UNIVERSITÀ DEGLI STUDI DI PADOVA
Corso di laurea in
Scienze e Tecnologie per l'Ambiente e il Territorio

Evaluating nitrogen variable rate technology on cotton (Gossypium hirsutum L.) in Georgia (USA). Unicuique suum.

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Georgia,
Georgia,
The whole day
through,
Just an old
sweet song
keeps Georgia
on my mind...
S.G & H.C

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Abstract

The project aimed to apply and test Variable Rate Application (VRA) advantages on cotton. Cotton requires application of different agronomic practices such as defoliants and fertilizers. While defoliants facilitate harvesting operations, fertilizers assure an optimal plant growth. In particular, pre-planting fertilization guarantees a good seed germination whereas mid-season side-dressing fertilization influences bolls forming and so it is a key factor for lint and seeds production. Prediction of crop potential growth helps farmers to plan appropriate mid-season fertilizer applications, resulting in reduction of cultivation costs and mitigation of fertilizer pollution (i.e. nitrate).

It is widely known that cotton is one of the driving crops of Georgia economy. Despite it has a long cropping history in this State, nowadays precision agriculture, and in particular nitrogen variable rate application (VRA) , offer new opportunities to optimize crop cultivation .

VRA is a precision agriculture technique that allows modulating agronomic input according to soil variability observed in the field. Basically there are two methods to manage variability: a) pre-developed application or prescription maps; b) real-time sense and treat systems. In general the first approach is more reliable and consequently more popular among the farmers. However the development of proximal-sensing technologies is increasing the interest toward the real-time method.

The main aim of this study was assessing agronomic, economic and environment profitability of nitrogen VRA on cotton based on Normalized Difference Vegetative Index (NDVI). A secondary goal was to evaluate the GreenSeeker spectroradiometer as a tool for managing VRA of cotton agrochemicals in Georgia.

The experiment was carried out in 2011 during the growing season. The experimental site was a 8-ha field located in Tift County. Soil variability was assessed through pre-planting soil analysis integrated by soil electrical conductivity (ECa) measurements.

Proximal sensing was carried out during the crop season using the spectroradiometer GreenSeeker®. The sensor permits to measure the Normalize Difference Vegetation Index (NDVI). NDVI is a vegetation index based on near infrared and red wavelengths leafs chlorophyll reflection. The index is sensitive to leaf chlorophyll amount and so it is an effective indicator of plant biomass. Maps of NDVI were obtained connecting GreenSeeker® with on board truck's computer and GPS systems.

VRA N fertilization was based on prescription maps obtained applying Sensor Based Nitrogen Rate Calculators (SBNRCs) method developed by Clemson University to previous sensed NDVI map.

Prescription map was first built by Farmwork® software and then loaded in a variable rate applicator system for side-dress N fertilization.

Finally, yield map was obtained at the end of the growing seasons by an yield mapping system mounted on a cotton picker.

Results showed as VRA provided crop yields comparable to conventional fertilization allowing at the same time to reduce N input and to increase N efficiency.

Variable nitrogen rate application seems to be a valuable and profitable techniques to sustain cotton productivity in respect of the environment.

Riassunto

La finalità di questo studio è stata di applicare la tecnica di tassi variabili d'applicazione (VRA) alla coltivazione del cotone e successivamente di testarne i possibili vantaggi.

La coltura del cotone richiede l'impiego di diverse pratiche agronomiche come l'applicazione di ormoni defolianti e la distribuzione di fertilizzanti; la defoliazione facilita le operazioni di raccolta, i fertilizzanti assicurano una produzione ottimale. In particolare, una fertilizzazione pre-semina assicura la germinazione del seme e l'emergenza della pianta, mentre una fertilizzazione in copertura risulta essere il fattore chiave nella produzione di fibra e semi. La possibilità di poter predire un potenziale produttivo delle piante permette un'appropriata fertilizzazione in copertura massimizzando la produzione e mitigando gli effetti inquinanti legati all'impiego di nitrati.

Il cotone rappresenta una delle principali fonti di reddito nell'economia della Georgia e nonostante abbia una lunga storia agronomica, l'agricoltura di precisione e in particolare l'applicazione di tassi variabili (VRA) di fertilizzanti azotati offre nuove opportunità produttive. Il VRA permette di modulare gli inputs agronomici seguendo la variabilità del suolo e la successiva eterogeneità produttiva osservabile in campo. Principalmente i metodi che consentono di gestire tale variabilità sono: a) l'applicazione di mappe di prescrizione sviluppate attraverso i dati delle precedenti stagioni di coltivazione; b) l'analisi della variabilità e l'applicazione di trattamenti che avvengono simultaneamente durante la stagione produttiva (metodi *real-time* od *on-the-go*). Generalmente il primo approccio è più facilmente realizzabile e quindi più diffuso tra gli agricoltori. Tuttavia lo sviluppo di proximal-sensing (intesa come l'osservazione delle informazioni a distanze sub-metriche e basata sull'utilizzo di sensori) sta aumentando l'interesse nei confronti di metodi in *real-time*.

Lo scopo principale di questo studio è stato quello di valutare i vantaggi agronomici, economici ed ambientali della tecnica VRA riguardante la fertilizzazione azotata in copertura (NVRA); tali applicazioni sono state applicate in base alle analisi dell'indice di vegetazione normalizzato (NDVI). Un secondo scopo è stato quello di valutare lo spettrometro GreenSeeker® come strumento per realizzare il VRA nella coltura del cotone in Georgia.

L'esperimento è stato condotto durante la stagione produttiva del 2011. L'area

interessata dal sito sperimentale ha riguardato un campo di circa 8 ha situato nella città di Tifton, contea di Tift (GA). La variabilità del suolo è stata analizzata precedentemente la semina attraverso analisi chimiche e successivamente integrate con misure di conduttività elettrica del suolo (ECa).

Il proximal sensing dell'NDVI è stato realizzato tre volte durante la stagione di crescita del cotone usando lo spettroradiometro GreenSeeker®. L'NDVI è un indice vegetazionale basato sulla riflessione da parte delle foglie di lunghezze d'onda di luce rossa e infrarossa. L'indice è sensibile al contenuto fogliare di clorofilla il quale è direttamente collegato alla quantità di biomassa prodotta dalla pianta. Sulla base di questo rilevamento, essendo i sensori GreenSeeker® connessi ad un computer installato su un trattore e ad un sistema GPS, è stato possibile costruire delle mappe di dati NDVI georeferenziate.

L'applicazione dei diversi tassi di fertilizzante (NO_3^-) è stata successivamente basata su mappe di prescrizione ottenute tramite il "*Sensor Based Nitrogen Rate Calculator*" (SBNRC); l'SBNRC è un metodo di calcolo di tassi d'applicazione basato su un algoritmo sviluppato presso l'Università di Clemson (South Carolina, USA).

Le mappe di prescrizione sono state primariamente composte attraverso il software FarmWork® e successivamente comunicate al trattore per le concimazioni in copertura, implementato da un sistema di controllo capace di modulare i flussi di nitrato applicati (Variable Rate Technology). Alla fine della stagione di coltura è stata ottenuta una mappa di produzione georeferenziando i dati di raccolta.

I risultati hanno mostrato che le pratiche VRA hanno prodotto quantitativi di fibra e semi di cotone comparabili a quelli delle tecniche colturali tradizionali, permettendo allo stesso tempo di ridurre gli input di fertilizzante, ma aumentandone l'efficienza.

L'applicazione di tassi variabili sembra dunque una tecnica interessante e proficua che può sostenere la produttività della cultura del cotone nel rispetto dell'ambiente.

1. Introduction

1.1 Agriculture ecological footprint

In the last decades increasing attention has been given to the relationship between high fertilization inputs in agriculture and environmental risks. Over the past 50 years agriculture has been crucial in meeting the challenge of increasing food production faster than population growth; this phenomenon, throughout a set of technologies, has come to be known as the *green revolution* (FAO, 2003).

Impacts of green revolution and contemporary intensive agriculture new technologies (e.g. high synthesized fertilizers and pesticides inputs, mechanization etc.) on environment were largely ignored and led agriculture to be the largest consumer of water, the main source of nitrate pollution of groundwater and surface water, as well as the principal source of ammonia pollution. Intensive agriculture is also a major factor contributing to the phosphate pollution of waterways (OECD, 2001) and the release of greenhouse gases (GHGs), methane and nitrous oxide, into the atmosphere (IPCC, 2001).

Most of the negative impacts from agriculture on the environment can be reduced or prevented by an appropriate mix of policies and technological changes. This topic in 1990 saw the born of *sustainable agriculture* concept that is related to "an integrated system of plant and animal production practices having a site-specific application that will, over the long term (Food, Agriculture, Conservation, and Trade Act of 1990 (FACTA), Public Law 101-624, Title XVI, Subtitle A, Section 1603 (Government Printing Office, Washington, DC, 1990) NAL Call # KF1692.A31 1990):

- satisfy human food and fiber needs;
- enhance environmental quality and the natural resource base upon which the agricultural economy depends;
- make the most efficient use of nonrenewable resources and on-farm resources and integrate, where appropriate, natural biological cycles and controls;
- sustain the economic viability of farm operations;
- enhance the quality of life for farmers and society as a whole".

Therefore, relevant and sustainable technology innovation started to be planned and developed, with principle that productivity cannot be the sole criterion to guide agriculture technology development. The goals of these technologies were discussed in the FAO report (2003) and can be summarized as:

- increasing productivity of the most important food crops both on the more fertile soils and on marginal lands;
- more precise use of soil, water and nutrients in optimized integrated management systems.

In this context precision agriculture, merging technologies borne of the information age with a mature agricultural industry, could represent an answer; it allows an integrated crop management system that attempts to match the kind and amount of inputs with the actual crop needs for small areas within a farm field (Singh, 2007) and looking for an optimum profitability, sustainability and protection of land resources. This goal is not new, but new technologies now available allow the concept of precision agriculture to be realized in a practical production setting (Singh, 2007).

1.2 Precision Agriculture

Precision agriculture, also called precision farming, can be defined as an "application of technologies and principles to manage spatial and temporal variability associated with all aspects of agricultural production for the purpose of improving crop performance and environmental quality" (Pierce and Nowak, 1999).

Precision farming aims the increase efficiencies that can be realized by understanding and dealing with the natural variability found within a field. The goal is not to obtain the same yield everywhere, but rather to manage and distribute inputs on a site specific basis to maximize long term costs/benefits (Singh, 2007). Indeed, with the increase of input costs and decreasing commodity prices, farmers are looking for new ways to improve efficiency and cut the costs. Precision farming technology would be a viable alternative to improve profitability and productivity (Singh,2007).

Before the completion of agricultural mechanization, the very small size of fields allowed farmers to vary treatments manually. However, with the enlargement of fields and intensive mechanization, it has become increasingly more difficult to take into account of within-field variability without a revolutionary development in technologies (Zhang et al., 2002).

Instead the precision agriculture enables farmers to follow the variability of the field conditions and therefore to optimize the use of agrochemicals (e.g. fertilizers or pesticides) on real needs of different uniform areas of the field (Verghagen and Bouma, 1997). These techniques involve the re-organization of agricultural systems towards a low-input, high-efficiency and sustainable agriculture (Zhang, 2002). The aim of these techniques is (Robert et al., 1993):

- increasing yield production with same inputs amount;
- reducing inputs amount with the same yield production;
- increasing yield production while decreasing inputs amount.

Success of precision agriculture depends on different factors, including (Pierce and Nowak, 1999):

- the extent to which conditions, within a field, are known and manageable;
- the adequacy of input recommendations;
- the degree of application control;
- the degree of support through private and public infrastructures.

Precision agriculture is already a feasible and useful technology in terms of automation, data process and management, even if it faces with unresolved aspects that limits its application, as the scale precision that is required in space and the time variability of pedological and biological factors related to soil fertility (e.g. Morari et al. 2004). However this farming management technique has been already used successfully in several agricultural fields, both in terms of improvement of environmental quality and increase of economic viability. Precision agriculture, allowing farm production tracking and tuning, permits farmers to make economic analyses based on the variability of crop yield in a field in order to obtain an accurate assessment of risks (Zhang et al., 2002).

One of the most studied applications of precision agriculture is site-specific application of nitrogen. Ferguson et al. (1998) observed that an optimal N management within the field helps to reduce the environmental impacts of over-fertilization. Zhang et al. (2002) revealed positive effects of precision agriculture on nitrogen pollution. Indeed nitrate leaching was lower in potato cropping systems, especially in coarse-textured soils.

Moreover a study conducted in two adjacent fields, one treated with traditional agriculture technique for nitrogen fertilizer and the other with precision agriculture, showed the positive effect of variable rate technology (VRT) in reducing the ground water contamination (Whitley et al., 2000). Other studies have found that when N is applied in site-specific way its costs are higher than conventional fertilization but its environmental benefits are much higher due to reduce N leaching (Wang et al., 2003; Bongiovanni and Lowenber-Deboer, 2004). Jacobsen et al. (1998) concluded that site-specific application for N do not have any significant benefits.

1.3 Technologies in precision agriculture

The enabling technologies of precision agriculture can be grouped into five major categories (Pierce and Nowak, 1999) :

Computers: precision agriculture requires the acquisition, management, analysis and output of large amounts of spatial and temporal data. This type of farming practice has developed a mobile computing system with which trucks and tools are enhanced to function in on the go farming operations.

Global Position System (GPS): they are essential for precision agriculture to assess the spatial variability and for site-specific control. All phases of precision agriculture require positioning information and GPS is able to provide the positioning in a practical and efficient way.

Geographic Information Systems (GIS): they are defined as a collection of computer hardware, software, and geographic data for capturing, managing, analyzing, and displaying all forms of geographically referenced information (www.esri.com). GIS is a decision support system involving the integration of spatially referenced data in a problem-solving environment (Cowen, 1988). In fact the value of precision agriculture is transforming information into management decisions that increase profitability, benefits and environment (Pierce and Nowak, 1999).

Sensors: they are devices that transmit an impulse in response to a physical stimulus such as heat, light, magnetism, motion, pressure and sound. With a computer to record the sensor impulse, a GPS to measure position and a GIS to map and analyze the sensor data, any sensors output can be mapped at very fine scale. Wireless smart sensor array for measuring soil moisture offers new opportunities to apply precision irrigation. Indeed this technology allows for a large number of sensors to be installed in a field and provide data wirelessly to a centrally located receiver (Vellidis et al., 2007).

Sensors are critical to success in the development of a precision agricultural system for three important reasons: they have fixed costs, they can sample at very small scale of space and time and facilitate repeated measures. The potential use of ancillary data that can be intensively recorded, such as soil bulk electrical conductivity (EC) measured by electro-magnetic induction (EMI) surveys, has been well examined over the last decade. This is because data are relatively easy and inexpensive to collect. If the sparse and more intensive data are spatially correlated, then the additional information from the ancillary data can be used to improve the estimate precision of the sparsely sampled primary variable (Morari et al., 2009).

Application control: it is that part of automated system in which sensed information is used to influence the system's state in order to meet an objective .

For precision agriculture, control must be achieved in space and time for varying single or multiple inputs at different rates, at varying soil depths and in an uniform and location-specific manner within fields. Success of precision agriculture depends on reaching needed accuracy at the point of application of inputs (Pierce and Nowak, 1999).

Accuracy of application equipment is dependent on driving precision, uniformity of distribution, topography, field surface conditions, wind conditions and metering efficiency. Specific to Precision Agriculture are the transition time for change in rate or product and positioning or location control and those aspects of application in which changing rates or products affect variability in performance (Pierce and Nowak, 1999).

The major issues for precision application of inputs remain transition time for changes in product or rate, uniformity of application, and rate increment control.

1.4 Variable Rate Application (VRA)

Variable rate application is a practice based on sensor systems with the aim to optimize and maximize yields and returns. It consists in manage the crop inputs applying in the field optimized quantity of agrochemicals with the goal to prescribe a variable rate application according to soil and crop needs (Roberts et al., 2002). VRA can be involved in plant growth regulators, defoliant, pesticides, water and nitrogen applications.

1.4.1 Application paths

VRA usually followed two main paths (Taylor and Fulton, 2010). One path is a map-based approach that is developed from historical information of previous crops data; those data are processed through an expected crop response algorithm on which to plan a prescription map to variable rate application. With available technologies of GPS, remote sensing, yield monitoring, and soil sampling, the map-based approach is generally easier to implement (Zhang et al., 2002).

The second path is based on real-time sensors; with this technique data are collected during the cropping season from sensors; information are processed, interpreted by on-board computer and simultaneously applied to the crop.

Also the real-time sensing approach uses a predetermined algorithm to convert data in an application rate which is subsequently used to build a prescription map.

This path in farming tillage allows to sense and apply supplies in the same time of sensing procedure; our approach was different and prescription map was built on different sensing maps detected in different crop's growing stages.

1.5 The cotton in Georgia

Cotton tillage drives a central role in south US states agriculture economy. Planting areas designed for cotton change year by year depending on trading price of other crops and on general demand. South west of the United State is generally the greatest American cotton producer (*Figure 1.1*).

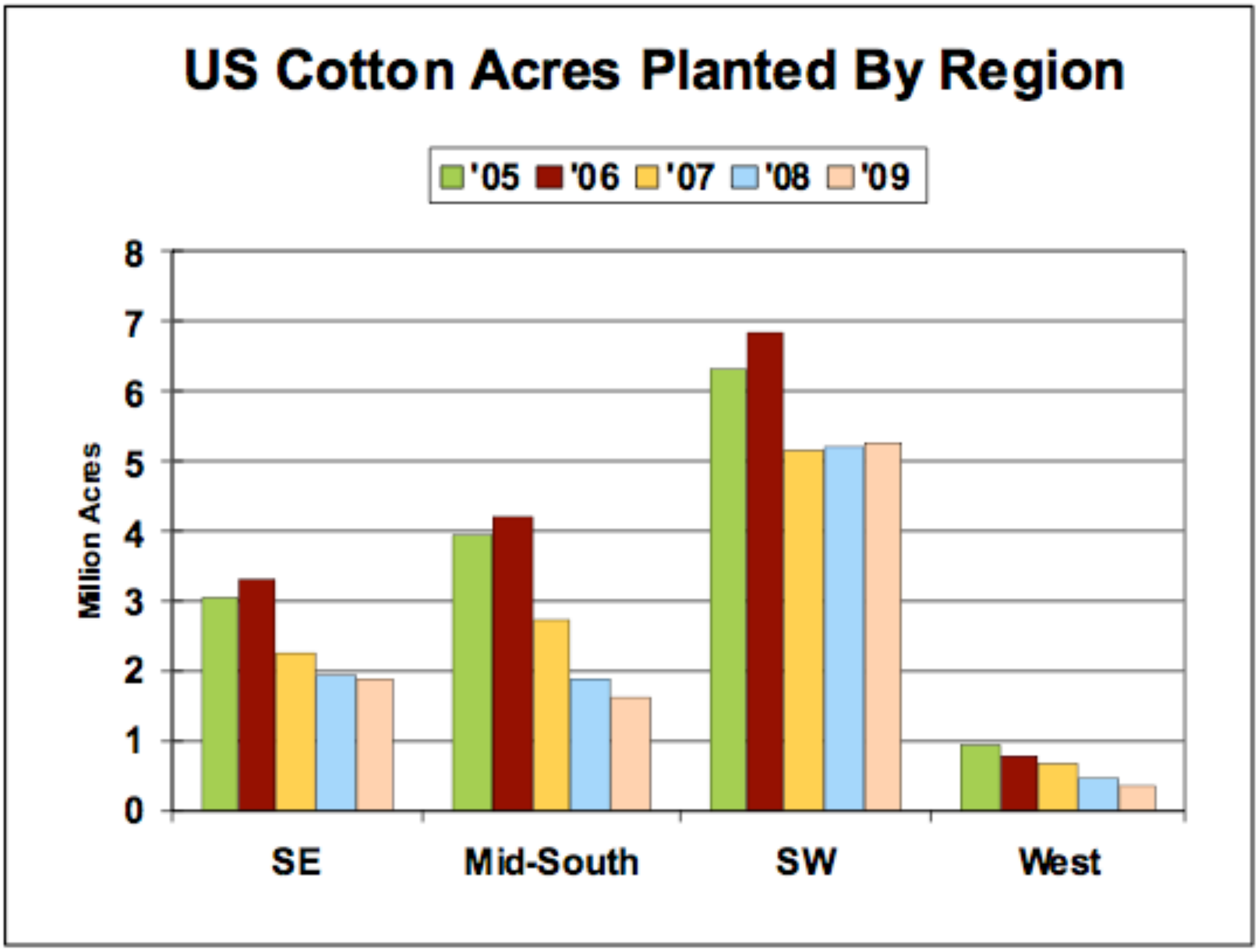


Figure 1.1 – Last years US cotton planting situation (ugacotton.com); 1 acre = 0.4047 hectare

Despite the largest West US cotton production, every years Georgia sees in average more than 1 billion acres (more than 404000 hectares) of tillable land interested from cotton production. Economic value (between lint and seed) is above 1 billion $ (georgiacottoncommission.org) (*Figure1.3 and 1.4*).

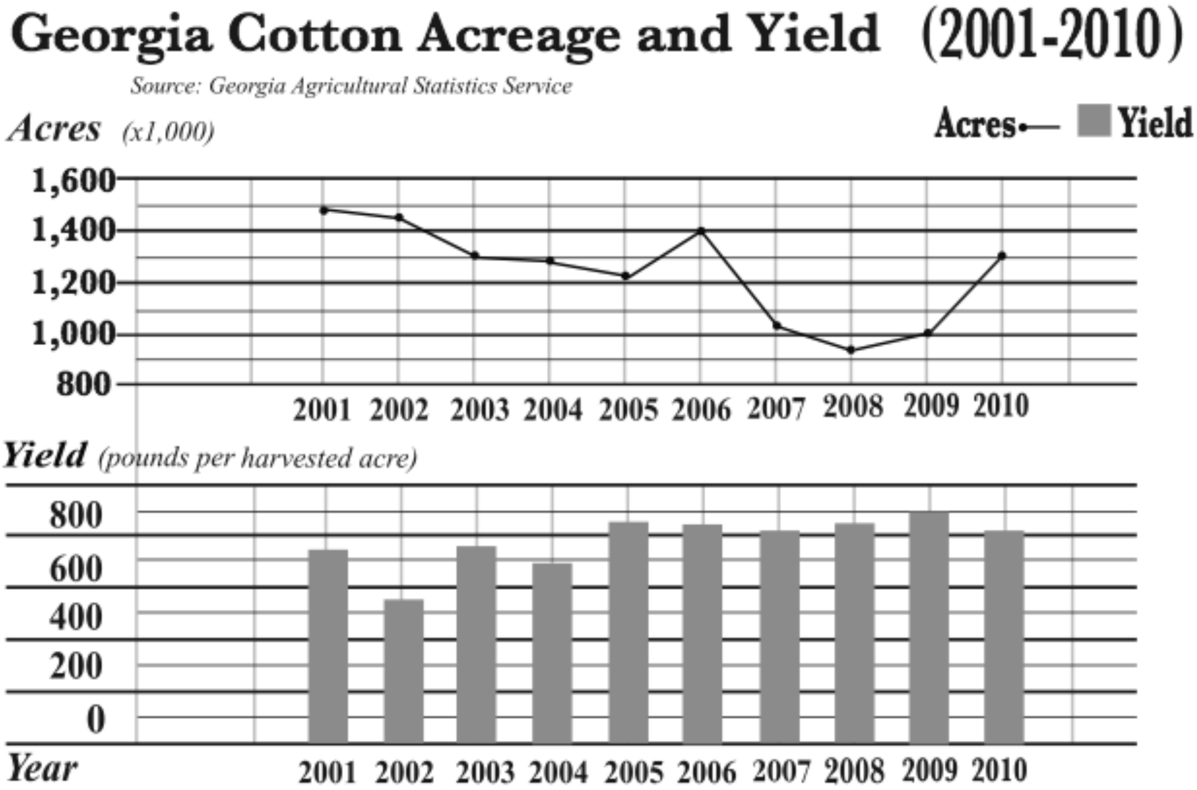


Figure 1.3 – Past 10 years record of cotton seedling acreage and yield (georgiacottoncommission.org); 1 acre = 0.4047 hectares; 1 pound = 0.4536 kg

In the last three years cotton acreage has declined. 40% less plantings was mainly due to high prices and higher net returns for competing crops such as corn and soybeans (ugacotton.com). Even if cotton is an historical crop for United States and specially for Georgia, its production still faces great challenges due to the complex managing that this crop needs for growing.

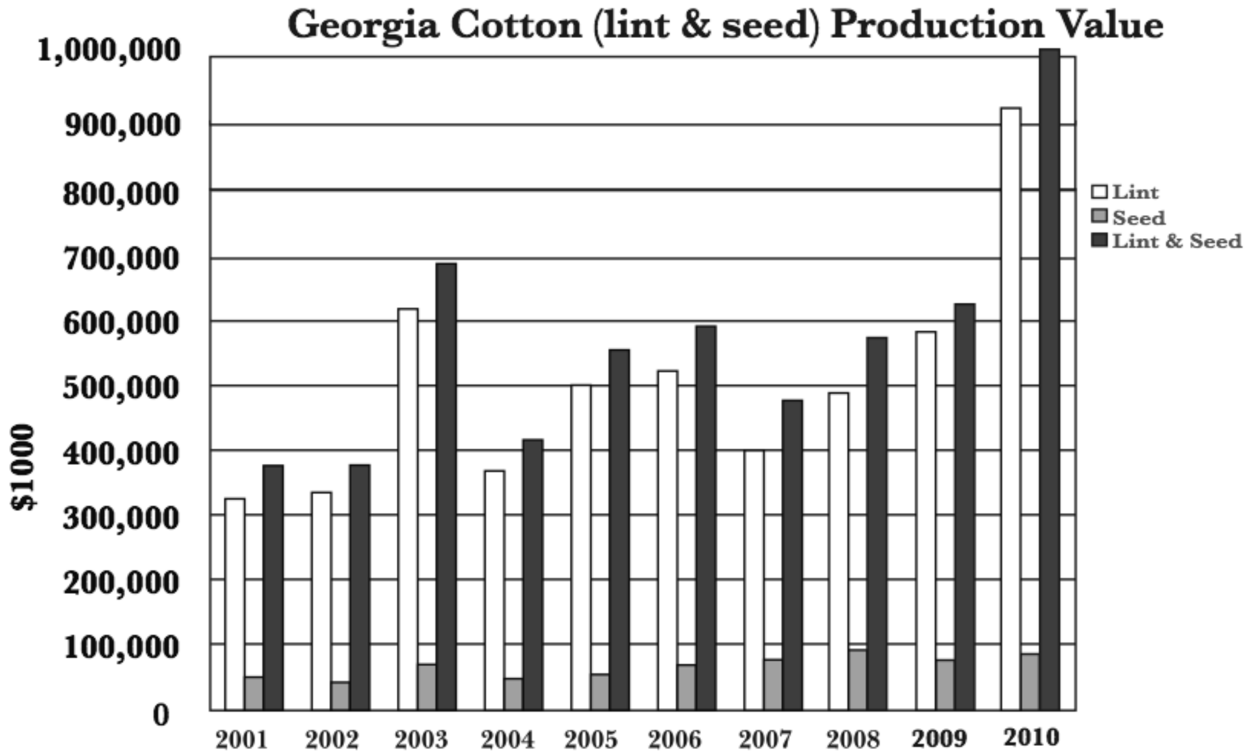


Figure 1.4 – Past 10 years Georgia cotton production trend (georgiacottoncommission.org)

1.6 Objectives

The main aim of this work was to assess economic and environmental profitability of managing nitrogen fertilization with precision agriculture technique applied to cotton crop.

Specific objectives were:

- testing variable rate technology, as a specific precision agriculture method, on cotton crop;
- testing Normalized Difference Vegetation Index (NDVI) in order to quantify different fertilizer variable rates (i.e. nitrogen);
- evaluating cotton efficiency response to site specific fertilization.

2. Materials and Methods

2.1 Experiment field

The experimental site is located in Tifton, Georgia; Tifton city belong to Tift county, in the south part of Georgia, about 100 km far from Florida's north border (*Figure 2.1*).

Figure 2.1 - Tifton town position

The experiment was carried out from May 2011 to November 2011. Daily temperature was on average 25.8 °C with a minimum of 19.5 °C and a maximum of 32 °C, higher than historical 100-yr period data: average 24 °C, minimum 18°C and maximum 30 °C. Highest and lowest temperature peaks were 38 °C and 11 °C respectively.

Rainfall was 586 mm, slightly higher than the last century record for the same period (520 mm on average; georgiaweather.net).

The experimental field size was about 8 ha. Top soil layer was sampled in 98 points according to a irregular grid scheme and analyzed for the main chemical properties (*table 2.1*).

Apparent electrical conductivity (ECa) of shallow and deep profiles was measured in the field with Veris 3100 associated to a DGPS .

Table 2.1 – Soil main chemical properties

	Average	*Standard Error*
pH	*7.01*	*0.03*
Ca_{exc} *(kg /ha)*	*874.37*	*21.56*
K_{exc} *(kg /ha)*	*151.28*	*4.07*
Mg_{exc} *(kg /ha)*	*158.39*	*4.76*
Mn_{exc} *(kg /ha)*	*10.33*	*0.21*
P_{lab} *(kg /ha)*	*71.03*	*3.36*
NO3-N (kg /ha)	*0.83*	*0.04*

Cotton was planted on May 25th 2011 and harvested on November 1st 2011. The factorial combination of four N treatments × 2 level of water input was tested.
A common pre-planting fertilization of 22.4 kg N ha^{-1} was applied in ammonium form (NH_4^+) to minimize leaching losses.
The four N treatments were (see also table):

1) N-Rich treatment: side-dressing N fertilization of 124 kg N ha^{-1} applied on June 8th, 14 days after crop planting (*Figure 2.2)*; high fertilization input in N-Rich was considered in order to avoid N stress and apply VRA algorithm (see equation 2), not taking into account the possible over fertilization. Total kg N ha^{-1} input = 146.4 kg N ha^{-1}.

Figure 2.2 – Dots correspond to georeferenced recording of nitrogen rich strips application (June 8th 2011)

2) Control treatment: side-dressing N fertilization of 95.3 kg N ha^{-1} applied on July

7th ;

Total kg N ha^{-1} input = 117.3 kg N ha^{-1}. N input is the conventional N amount applied on cotton in Georgia by farmers.

3) Variable rate application type 1 (VRA1): side-dressing N fertilization of 60.4 kg N ha^{-1} applied on July 7th;; N input was calculated implementing Sensor Based Nitrogen Rate Calculator using Clemson algorithm (see below). Total kg N ha^{-1} input = 82.8 was applied.
4) Variable rate application type 2 (VRA2): side-dressing N fertilization of 76.2 kg N ha^{-1} applied on July 7th;; N input was calculated implementing Sensor Based Nitrogen Rate Calculator using a experienced-based algorithm (Vellidis, 2011). Total kg N ha^{-1} input = 98.6 was applied.

Table 2.2 – Nitrogen prescribed per each treatment (N rate) and total amount including preplanting rate (Total N applied)

Treatment	*N rate (kg N ha^{-1})*	*Total N applied (kg N ha^{-1})*
N-Rich	*124*	*146.4*
Control	*95.3*	*117.3*
*VRA1**	*60.4*	*82.8*
*VRA2**	*76.2*	*98.6*

*N rate applied relative to VRA1 and VRA2 will be discussed successively in paragraph 3.2 and 3.3.

The side-dressed fertilizer was UAN (N 28%) with the following composition: 40% ammonium nitrate; 30% urea; 30% water.

Field was irrigated with two pivot systems. Two levels of water input were considered: lower water input (LW) and higher water input (HW) (*Figure 2.3*). Higher irrigation resulted from the overlapping of the two pivot systems. The experimental design can be assumed as an incomplete strip-block with 5 replicates.

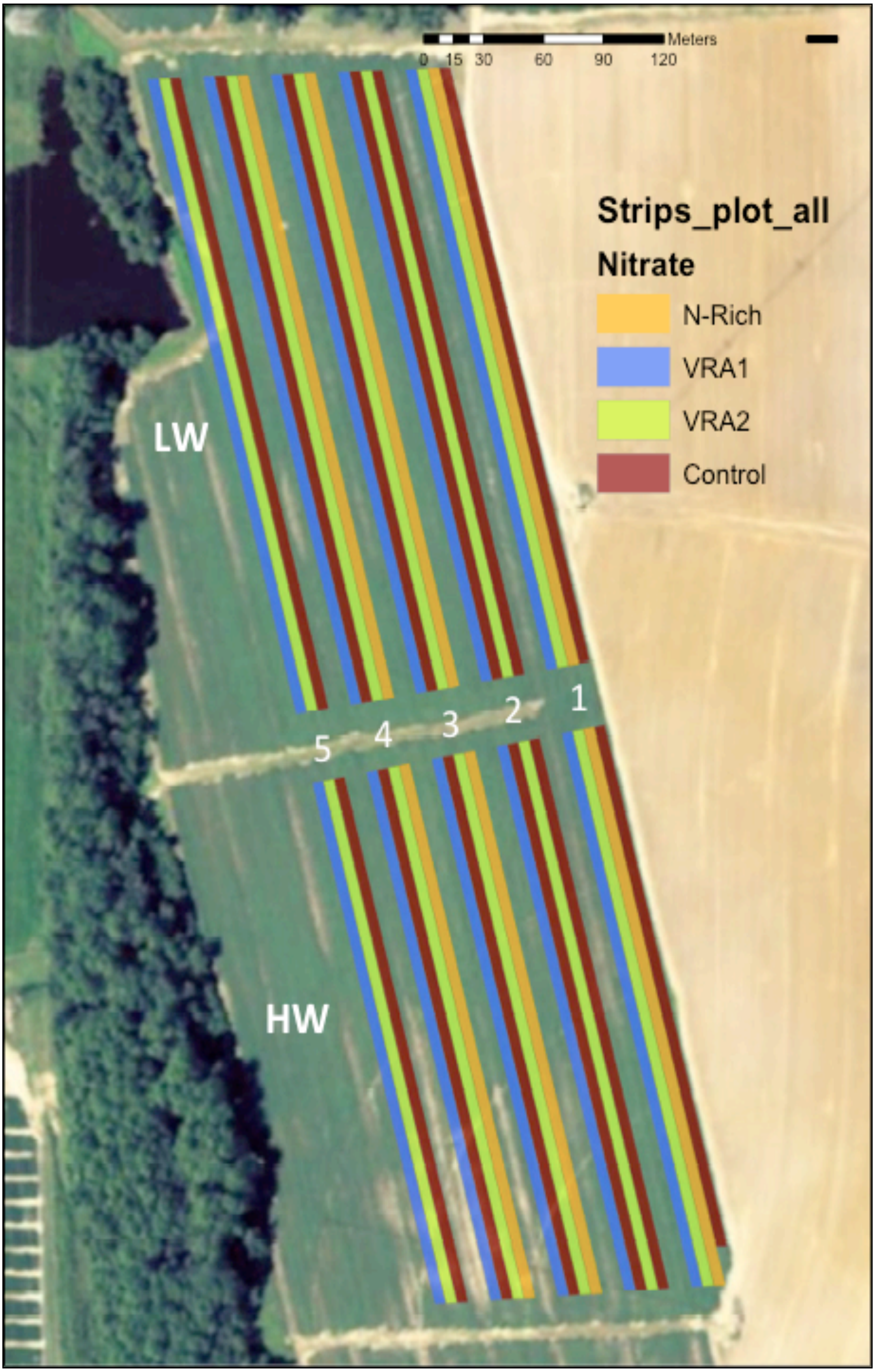


Figure 2.3 - Experimental field

2.2 Variable Rate Technology

Nitrogen application was driven by a LMC lay by rig platform with a Capstan NJect variable rate applicator operated by a 7700 John Deere tractor with a AGleader® insight rate controller.

Variable rate technology (VRT) adds to conventional sprayer GPS, *VRT controller*, *feedback control loop* and a *return line* (*Figure 2.4*).

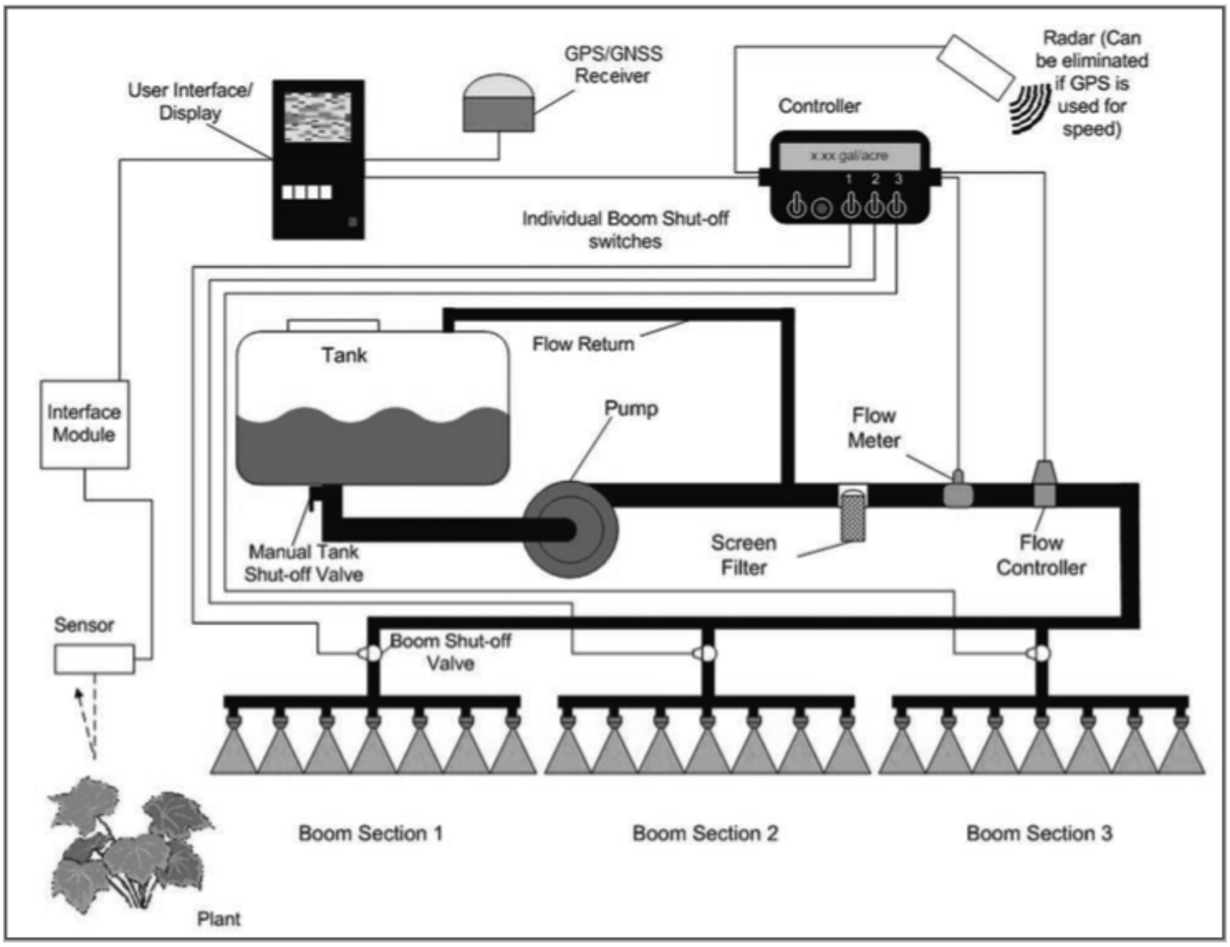


Figure 2.4 – Variable rate technology scheme, from detection to application

VRT controller and feedback control loop process and control the application rate. They can be a separate system from the software and control mechanism. It uses the set point rate from the software and ensures that the control mechanism (motor or actuator) puts out the appropriate rate. It uses feedback from a ground speed radar (GSR) or other speed sensor to compensate for speed variations, while also using a speed or position feedback from the control mechanism to ensure it is turning at the appropriate speed or positioned correctly (Timely Information, 2009). The system allows to change flow rate; it takes time for every VRT system to adjust actual flow rate to match the desired flow rate. This time as known as lag time and also when desired rate is achieved errors will occur. Thus there is a gap between prescribed rates and real applications. To reduce this undesirable gap is necessary an accurate system calibration (*Figure 2.5, 2.6*).

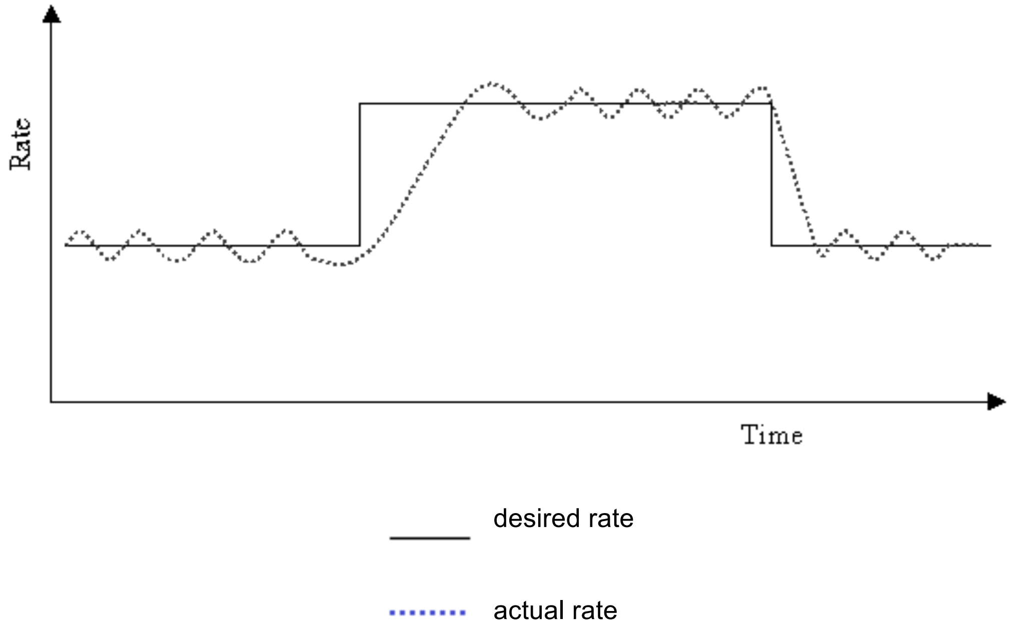


Figure 2.5 - Graph shows the flow lag time: real variation rate trend up to prescribed one (Timely Information, 2009)

Figure 2.6 – Sprayer calibration; it occurred calculating a prescribed flow rate of water in order to estimate the corresponding real emitted flow

Figure 2.7 - Nitrogen crop application in field

2.3 Normalized Difference Vegetative Index (NDVI)

VRA real-time sensing approach is commonly used in order to quantify the nutrient needs of the crops. The Normalized Difference Vegetative Index, commonly called NDVI, is a widespread index to assess whether the crops contain live green vegetation. The sensors operate above the crops and measure the reflectance of different colors (different light wavelengths) through which to obtain the index.

Reflectance data in visible, infrared, near infrared (and microwave) regions are correlated with cotton growth and plants structural indices (Amit Sharma et al., 2008).

NDVI is correlated with the cotton (and the most common crops) leaf properties of the spectral reflectance; in fact, green plants have relatively low reflectance (and transmittance) in the visible regions of the spectrum (400 – 700 nm) (*Figure 2.8*).

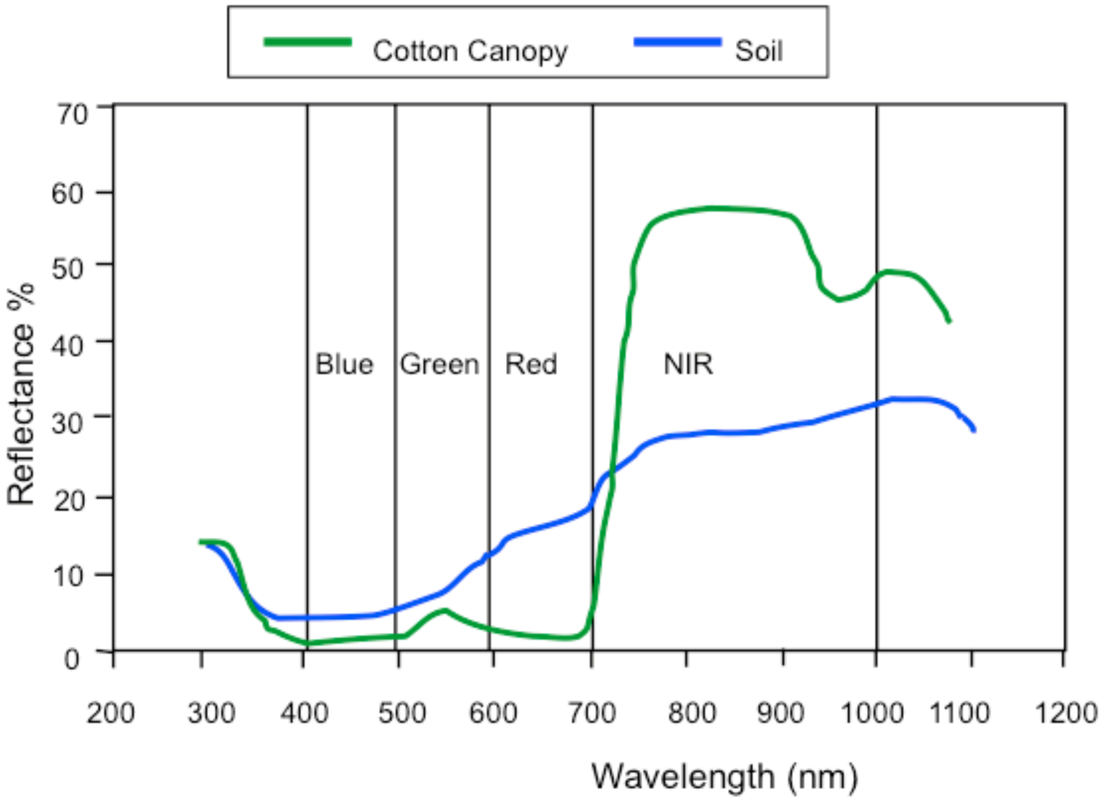


Figure 2.8 – Spectral reflectance of plant leaves and soil; reflectance peak at 550 nm typical of green vegetation and results in the green appearance of vegetation; dip at 650 nm corresponds to the absorption of red light by plant's chlorophyll

Low reflectance is caused by high absorbance of light by chlorophyll for photosynthesis. By contrast, green plant reflectance (and transmittance) is usually high in the near infrared (NIR) region (700 – 1300 nm) because of low absorbance of this part of the spectrum. This behavior it's possible to understand how leaves absorbance is correlated to chlorophyll concentration and so with greenness of plant. When chlorophyll concentration decreases, other leaf pigment can reflect visible light. This difference in reflectance properties between visible and NIR wavelengths is the basis for most remote sensing techniques for managing crops and measuring plant response throughout the season.

Mathematical relationship between reflected light in the visible and NIR wavelength often represent Vegetation indices (VIs). VIs provide a simple method for measuring plant response. NDVI is the most common and highly correlated used index (Tucker, 1979; Plant et al., 2000):

$$NDVI = \frac{NIR_{reflectance} - Red_{reflectance}}{NIR_{reflectance} + Red_{reflectance}}$$

(1)

Where NIR is referred to near infrared leaves reflectance and Red is referred to red wavelength light reflected by leaves.

NDVI performs exceptionally well (r^2=0.92) when goals require a quantitative method of biomass detection or leaf area index (Vellidis, 2011) (*Figure 2.9*).

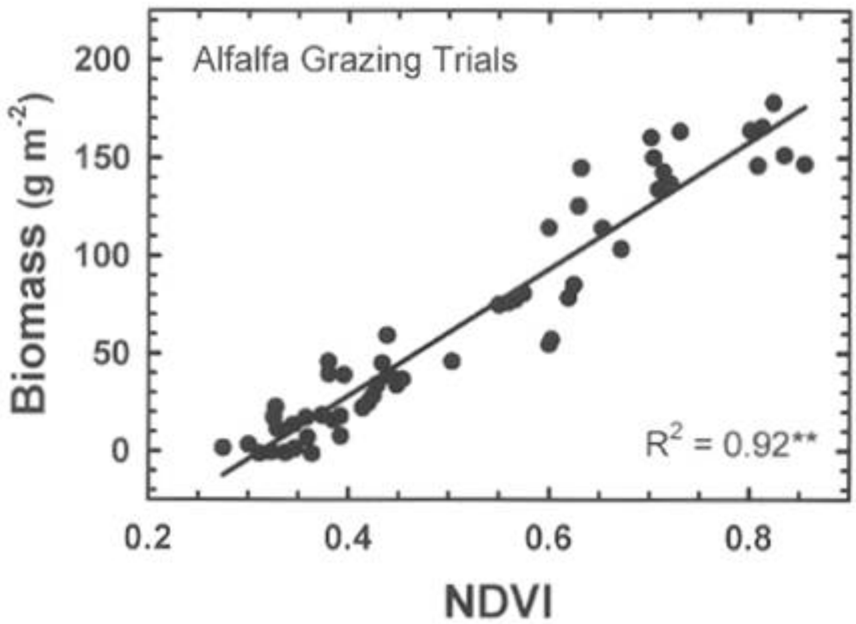


Figure 2.9 – Relationship between NDVI and biomass detection (Vellidis, 2011)

The importance of this high correlation is fundamental to understand plants nutrient requirement through which to create a prescription map for nitrogen variable rate fertilization. This practice generates interest since it can optimize profitability, sustainability and environmental protection through better utilization of nitrogen and reducing waste (Arnall et al., 2008).

2.4 NDVI sensing

NDVI was detected with GreenSeeker®. GreenSeeker® is an integrated optical sensing and application system that measures crop status on which set the variable nitrogen requirements.

NDVI sensors uses emitting diodes (LED) to generate red and NIR light; reflectance of the crop is measured by photodiode located at the front of sensor head (Gupta, 2008)

(*Figure 2.10*).

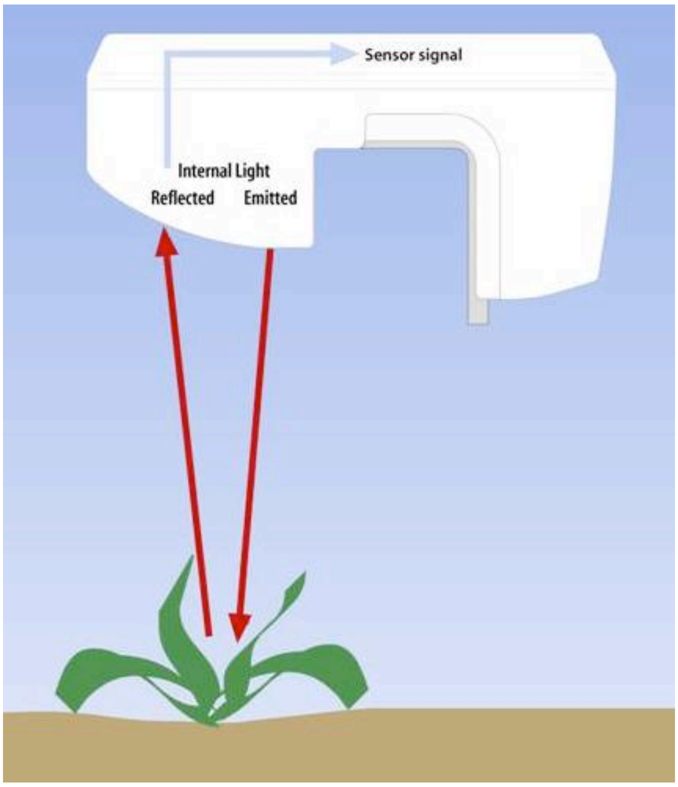


Figure 2.10 - GreenSeeker® sensor functional scheme

The sensors used for analysis are six GreenSeeker® sensors placed on a 6700 John Deere High Boy sprayer (*Figure 2.11*); sensors detect 91.44 cm (36 inches) row each, which is equal to a 548.64 cm (216 inches) total width sampling bar.

The truck speed during sensing was between 9.65 and 14.48 km/h (6.0 and 9.0 mph).

Figure 2.11 - John Deere High Boy sprayer equipped with GreenSeeker® sensors

Sensing and application stages were not contemporary. Sensing occurred three times: on June 21st, July 7th and the last on July 21st.

First two NDVI detections were made before side-dressing nitrogen application, the last one was made after fertilization.

2.5 Yield data

Yield data were measured by yield monitor mounted on John Deere 9965 cotton picker. It harvested 4 rows for a total width of 366 cm and an average speed of 6 km/h.

2.6 The Sensor Based Nitrogen Rate Calculator approach

A fertilization prescription map was made by mean of a Sensor Based Nitrogen Rate Calculator (SBNRC). This technique relies on placing preplant Nitrogen Rich Strips in farmer fields, whereby mid-season NDVI sensor readings are collected and a response index is successively determined. This index indicates the likelihood of obtaining a response to topdress N. Combined with crop and region specific models that predict the yield, N fertilizer rates are determined by projecting removal as a function of yield, known concentrations of N in the cotton seed, the respective N removal amounts (N fertilized and non-fertilized), the predicted responsiveness to applied N at each site using the response index (Ed Barnes, 2009). Therefore the aim and strength of SBNRC is to calculate yield potential at mid-season, based on the NDVI response and the following N application prescriptions. SNBRC needs four components:

- Yield Prediction model, or Yield Potential (YP);
- Response Index (RI);
- Nitrogen removal (%N);
- Nitrogen Use Efficency (NUE).

These elements are the component of the following algorithm:

$$\text{N Rate} = (\text{YPN} - \text{YP0}) * \%\text{N} / \text{NUE} \qquad (2)$$

Where N Rate is the optimal rate of fertilizer application that plants need; YPN is the potential yield relative to N-Rich treatment; YP0 is the potential yield relative to plants that are interested in variable rate treatment; %N is the nitrogen percentage in the crop harvestable part; NUE is defined as the Nitrogen Use Efficiency.
Equation (2) is known as the Nitrogen Fertilization Optimization Algorithm (NFOA) (Lukina et al., 2001).
SNBRCs tool are also available online (*Figure 2.12*) and allow farmers to calculate the amount of fertilization to apply.

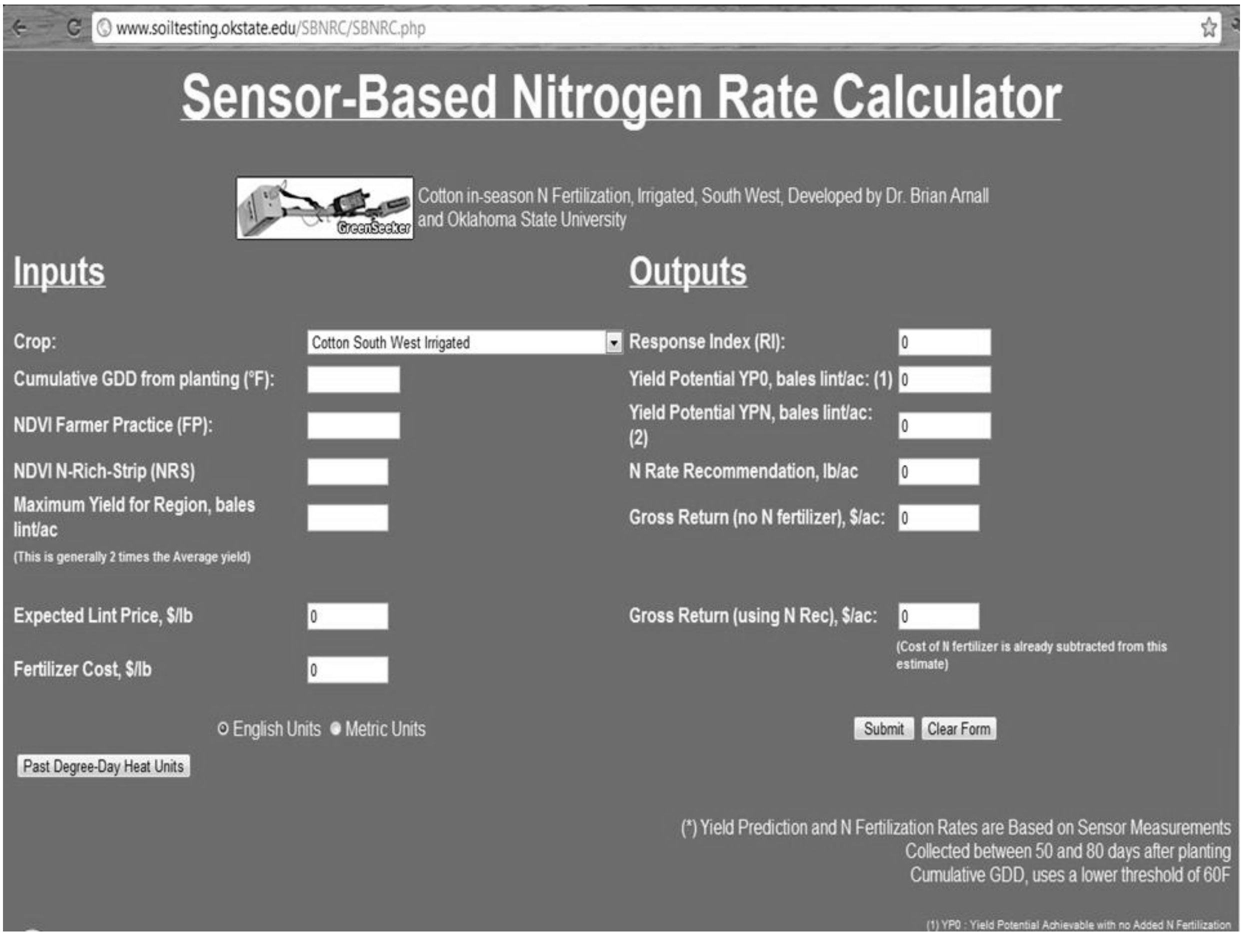


Figure 2.12 – Example of Sensor Based Nitrogen Rate Calculator available on web

2.6.1 Yield Potential

Yield Potential (YP0), predicted as a function of NDVI, is determined through the In Season Estimate of Yield (INSEY) index (*Figure 2.13*):

$$INSEY = NDVI / GDD \qquad (3)$$

where NDVI is referred to the field vegetation index data and GDD are Growing Degree Days. For cotton GDD are the days from planting to sensing (Arnal et al.,2008).

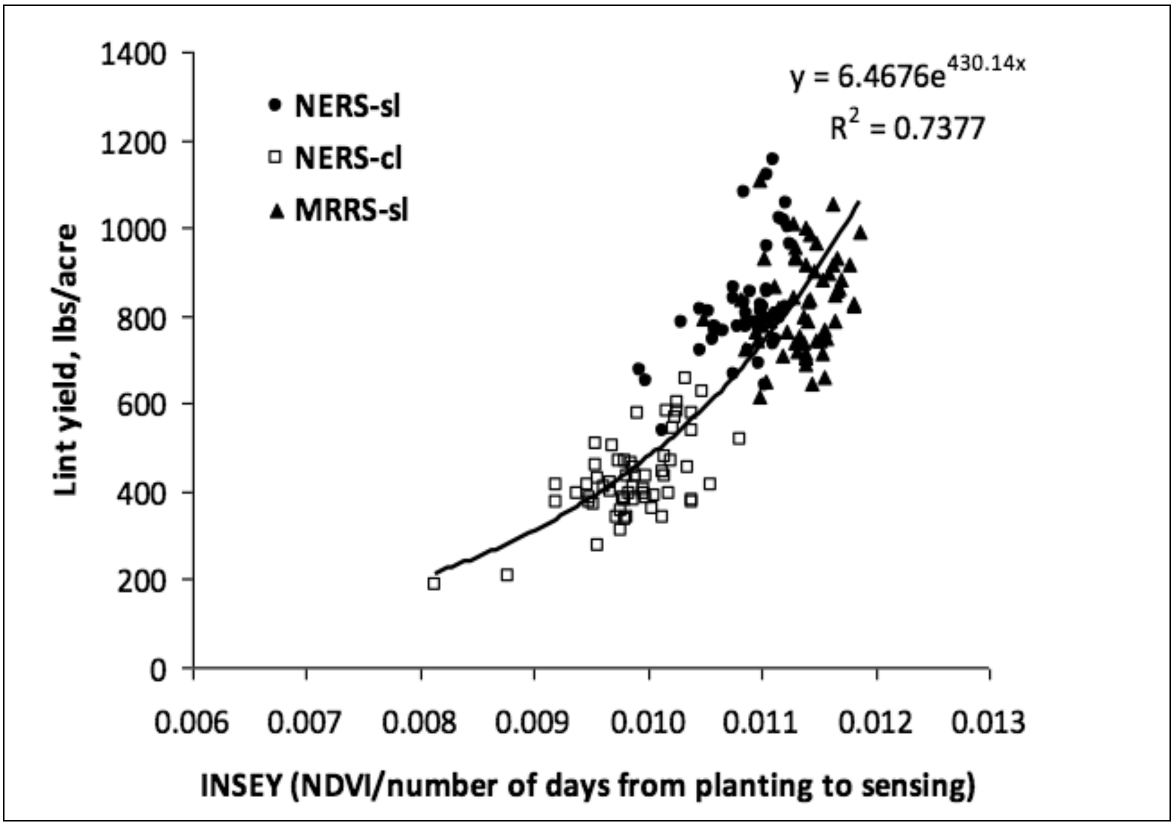


Figure 2.13 – Relationship between Yield and INSEY (Tubana, 2008 in: Ed Barnes, 2009) 1 lb = 0.4536 kg, 1 acre = 0.4047 hectare

INSEY is related to the biomass produced per day. To obtain a lint yield prediction from INSEY, the index is plugged into the following equation:

$$YP0 = 779.98 \times 10^{95.055 \times INSEY} \quad (4)$$

This equation is different for different environmental conditions, field location and crop managing. Yield prediction model (Equation 4), developed at Clemson University and concerning irrigated cotton, was used in this research for estimation of biomass production (Porter, 2010).

The predictable obtainable yield (YPN) with added nitrogen is then calculated multiplying YP0 by RI:

$$YPN = YP0 \times RI \quad (5)$$

2.6.2 Response Index

With Response Index (RI) is meant the response in yield to additional fertilizer nitrogen (Johnson and Raun, 2003). RI is calculated dividing NDVI of N-rich strips by the NDVI of field average (Arnal et al., 2008). This index gives us the response of the field to additional N fertilizer.

The importance of RI is that it can be determined mid-season (Hodgen et al., 2005 Mullen et al., 2003) by NDVI. RI is so obtained from:

$$RI = NDVI_{\text{N-RICH STRIPS}} / NDVI_{\text{FIELD AVERAGE}} \qquad (6)$$

2.6.3 %N and NUE

%N is the N percentage in lint production and its value is fundamental to understand fertilizer application prescription. Usually for a high-yield cotton crops %N is considered about 0.1-0.14 Kg N/kg of lint (Bassett et al., 1970; Mullins and Burmester, 1990; Unruh and Silvertooth, 1996).

The amount of N applied to the field is not equal to the amount of N taken up from the crop (Arnal et al., 2008). Nitrogen Use Efficiency, NUE is the approximate percentage of crop up-take and it ranges between 25% and 60% (Bassett et al,. 1970, Frischi et al,. 2004; Hou et al,. 2007; Janat 2005; Unruh and Silvertooth, 1996). This variability depends from soil, environmental zones, timing regiment and cultural practice.

2.7 Data analysis

First data elaborations were carried out with FramWorks® (Trimble Navigation Limited, 2009) and ArcMap™ (ESRI Inc., 1999-2010).

Classical ANOVA with proc mixed (SAS ver. 9.2) was applied to yield and N use efficiency data considering N type and water level as independent factors. Average strip data were obtained averaging the yield point data measured by the yield monitor.

NDVIs and yield data were then assessed considering their spatial variability and distribution by mean of geostatistical analysis. Geostatistics differently from classic statistics, assume that data are spatially interrelated and that these correlations can be expressed throughout relative distances between the collected points.

A spatial dependence presumes that collected point values are not randomly distributed but it presumes they have a spatial relationship; spatial relationship results so in the probability that loser points have closer values.

Objective of this analysis is thus to estimate the effect of points position up to their features variability. This geospatial elaboration is basic for further spatial prediction that allows an estimation of values and errors relative to predicted not measured positions.

Data spatial variability usually is assessed with the semi-variogramm (Figure 2.14); it allows to evaluate variability of points with increasing distances.

Semivariogramm is a geostatistical model used to measure semivariance relative to couple of observed data at fixed distances (lag) and direction.

Semivariance general expression is:

$$y(h) = \frac{1}{(2m(h))} \sum_{i=1}^{m(h)} (z(x_i + h) - z(x_i))^2 \qquad (7)$$

In which z is the value of a point, h is a distance range between a point and its lag and *m(h)* represents how many couples are observed at h distance.

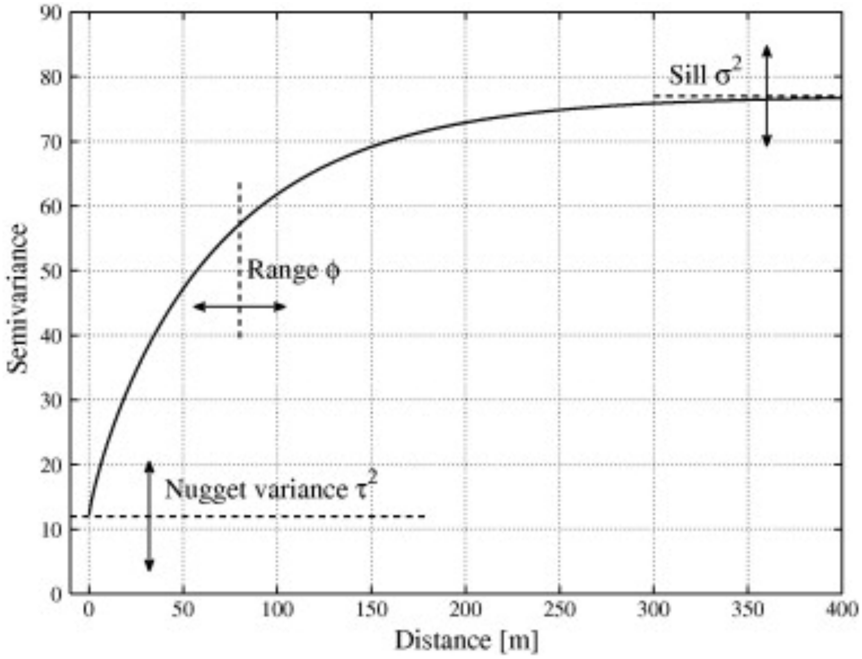


Figure 2.14 –Semivariogram model general scheme

Semivariogram graph (*Figure 2.14*) is outlined from parameters through which to achieve information about spatial behavior of analyzed variable:

- slope: it's the gradient of the first curve part and describes how much the variable value change up to the increasing spatial distance;

- sill: it represents the maximum value of the variance and so the possible field variability relative to detected variable;
- nugget: it indicates semivariance quote gave from random and spatial variability between lower distances than the minimum one used in data collection;
- range: it represents the higher distance in which is possible to find a spatial correlation between point semivariance, more over the range value it's not possible to find a correlation of data spatial variability.

Spatial correlations between variables are assessed also with cross-variogram tool.
Cross-variogram equation is the following:

$$y_{jk} = \frac{\Sigma(y_j(x) - y_j\ (x+h)\ (y_k(x) - y_k(x) - y_k\ (x+h))}{2N} \qquad (8)$$

In which $y_j\,(x)$ and $y_k(x)$ are the measure values of variables y and k of a x point and h is the distance between a point and its lag.

A Linear Model of Coregionalisation (LMC; Wackernagel, 2003) was applied to the three NDVIs datasets. The LMC assumes all the studied variables are the result of the same independent processes, acting at different spatial scales u. The $n(n+1)/2$ simple and cross semivariograms of the n variables are modeled by a linear combination of N_S standardized semivariograms to unit sill.
Kriging model was eventually used to build the maps of NDVIs and yield. Geostatistical analyses were carried out using ISATIS software (Geovariance and Ecole des Mines de Paris, 2008).

3. Results and discussions

Cotton yield showed poor correlation ($p<0.05$) with soil parameters (*Table 3.1*). In particular, negative values were observed with $CaCO_3$ (r = -0.21) and NO_3-N (r = -0.34) while positive values were observed with Mg_{exc} (r = 0.26) and P_{lab} (r = 0.29). Negative poor correlations were observed also for shallow (r = -0.24) and deep (r = -0.29) ECa.
Instead stronger correlations were found with NDVIs with the highest value (r = 0.6) for NDVI sensed on July 6th . Nitrogen petiole concentration appears to be an ineffective indicator to drive fertilization. Indeed it did not show any significant correlation with crop yield.

3.1 Geostatistical analysis results

Variograms showed a clear spatial correlation between the values sensed in the field (*Figure 3.1*). A unique spherical model with a range of 136 m and a nugget of 0.24 was identified for the three NDVIs. Sill varied according to the date. It was lower on June 21st than July 6th and 21st , most probably because of the early sensing time related with the primary plants growth stage (low field variability).
Low nugget values suggested also that GreenSeeker® sensors were robust and accurate tools.

Table 3.1 – Multiple comparisons between main soil and crop properties

	CaCO3	Ph_eq_water	Ca_Kg_ha	K_Kg_ha	Mg_Kg_ha	Mn_Kg_ha	P_Kg_ha	Zn_Kg_ha	NO3_N_Kg_ha	NDVI_6_21	Avg_NDVI_7_06	Avg_NDVI__7_21	EC_Deep	EC_Shallow	Yield	petiole_21_Jun_NO3	petiole_6_Jul_NO3	petiole_26_Jul_NO3
CaCO3	1.00	0.31	0.85	0.92	0.93	0.10	-0.55	0.26	0.48	-0.29	-0.30	-0.37	0.84	0.68	-0.22	-0.01	0.03	0.06
Ph_eq_water	0.31	1.00	0.57	0.31	0.49	0.32	-0.41	0.44	0.29	-0.13	-0.16	-0.29	0.33	0.34	-0.07	0.04	-0.04	0.22
Ca_Kg_ha	0.85	0.57	1.00	0.81	0.90	0.32	-0.35	0.58	0.49	-0.23	-0.17	-0.22	0.72	0.63	-0.14	0.15	0.18	0.27
K_Kg_ha	0.92	0.31	0.81	1.00	0.86	0.07	-0.57	0.26	0.47	-0.23	-0.19	-0.29	0.83	0.72	-0.10	-0.03	0.00	0.20
Mg_Kg_ha	0.93	0.49	0.90	0.86	1.00	0.14	-0.57	0.36	0.57	-0.26	-0.38	-0.45	0.81	0.66	-0.26	-0.07	-0.02	0.05
Mn_Kg_ha	0.10	0.32	0.32	0.07	0.14	1.00	0.36	0.49	-0.07	0.01	0.06	0.28	-0.06	-0.14	0.18	0.36	0.37	0.21
P_Kg_ha	-0.55	-0.41	-0.35	-0.57	-0.57	0.36	1.00	0.09	-0.43	0.29	0.42	0.61	-0.66	-0.64	0.29	0.38	0.38	0.14
Zn_Kg_ha	0.26	0.44	0.58	0.26	0.36	0.49	0.09	1.00	0.20	-0.12	0.02	0.05	0.19	0.20	0.03	0.32	0.33	0.39
NO3_N_Kg_ha	0.48	0.29	0.49	0.47	0.57	-0.07	-0.43	0.20	1.00	-0.29	-0.31	-0.37	0.50	0.44	-0.34	-0.09	-0.11	0.13
NDVI_6_21	-0.29	-0.13	-0.23	-0.23	-0.26	0.01	0.29	-0.12	-0.29	1.00	0.61	0.42	-0.34	-0.29	0.45	-0.58	-0.37	-0.31
Avg_NDVI_7_06	-0.30	-0.16	-0.17	-0.19	-0.38	0.06	0.42	0.02	-0.31	0.61	1.00	0.84	-0.35	-0.15	0.60	-0.06	0.05	0.12
Avg_NDVI__7_21	-0.37	-0.29	-0.22	-0.29	-0.45	0.28	0.61	0.05	-0.37	0.42	0.84	1.00	-0.49	-0.35	0.53	0.14	0.28	0.11
EC_Deep	0.84	0.33	0.72	0.83	0.81	-0.06	-0.66	0.19	0.50	-0.34	-0.35	-0.49	1.00	0.91	-0.30	-0.03	-0.12	0.16
EC_Shallow	0.68	0.34	0.63	0.72	0.66	-0.14	-0.64	0.20	0.44	-0.29	-0.15	-0.35	0.91	1.00	-0.24	0.00	-0.11	0.27
Yield	-0.22	-0.07	-0.14	-0.10	-0.26	0.18	0.29	0.03	-0.34	0.45	0.60	0.53	-0.30	-0.24	1.00	-0.10	0.01	0.17
petiole_21_Jun_NO3	-0.01	0.04	0.15	-0.03	-0.07	0.36	0.38	0.32	-0.09	-0.58	-0.06	0.14	-0.03	0.00	-0.10	1.00	0.55	0.59
petiole_6_Jul_NO3	0.03	-0.04	0.18	0.00	-0.02	0.37	0.38	0.33	-0.11	-0.37	0.05	0.28	-0.12	-0.11	0.01	0.55	1.00	0.36
petiole_26_Jul_NO3	0.06	0.22	0.27	0.20	0.05	0.21	0.14	0.39	0.13	-0.31	0.12	0.11	0.16	0.27	0.17	0.59	0.36	1.00

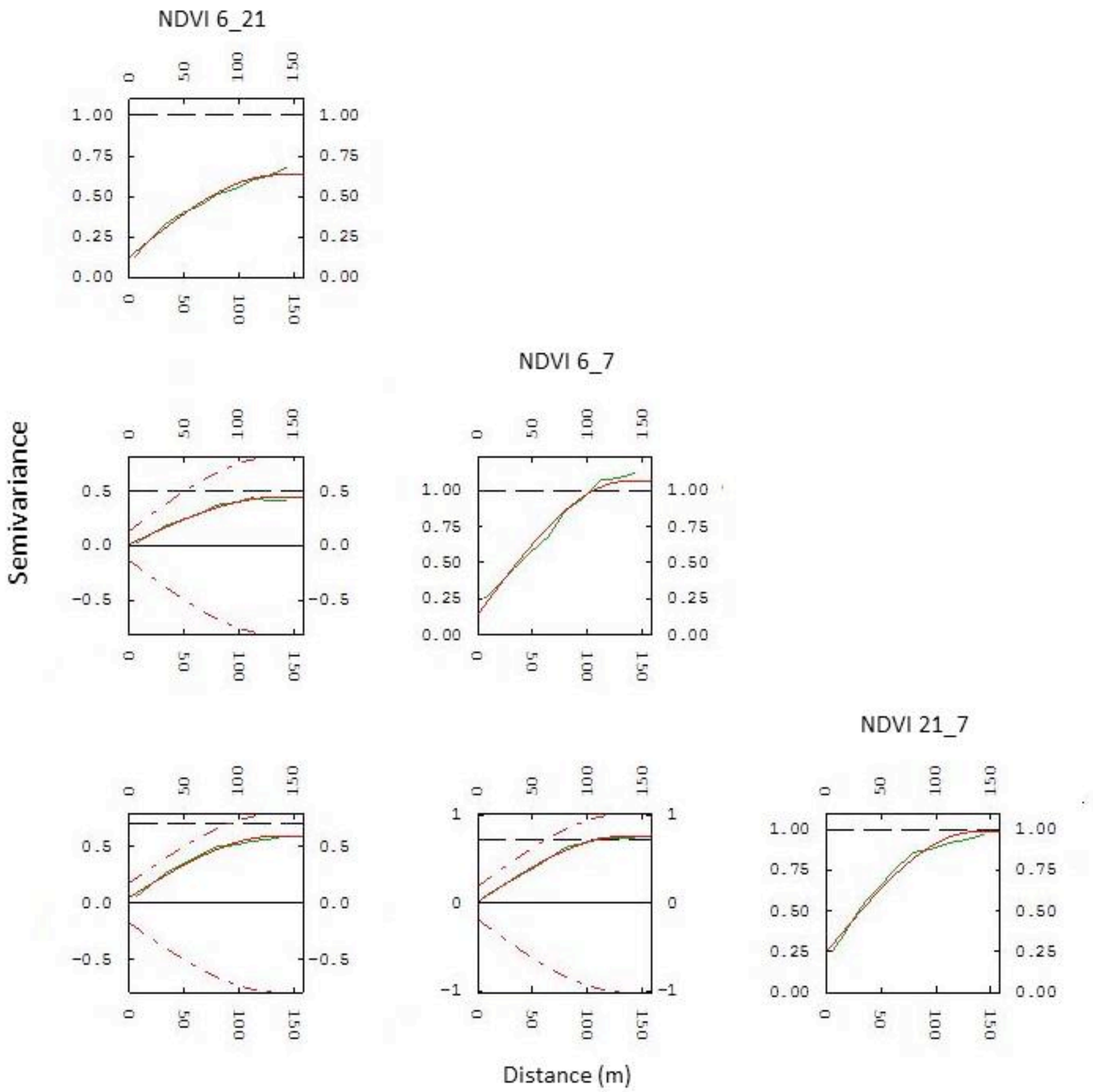


Figure 3.1 – Direct variograms and cross correlations relative to NDVI sensing of June 21st, July 7th and July 21st

Positive correlations were found between NDVIs at different sensing times (*Figure 3.1*). Cross-variograms also demonstrated strong spatial correlations between NDVIs. Therefore homogeneous areas in the field, identified by NDVI, persisted during the cropping season favoring the prediction of potential yield and the consequent fertilizer prescriptions.

Spatial models allowed the application of kriging in order to interpolate data and build NDVI maps (*Figure 3.2, 3.3, 3.4*).

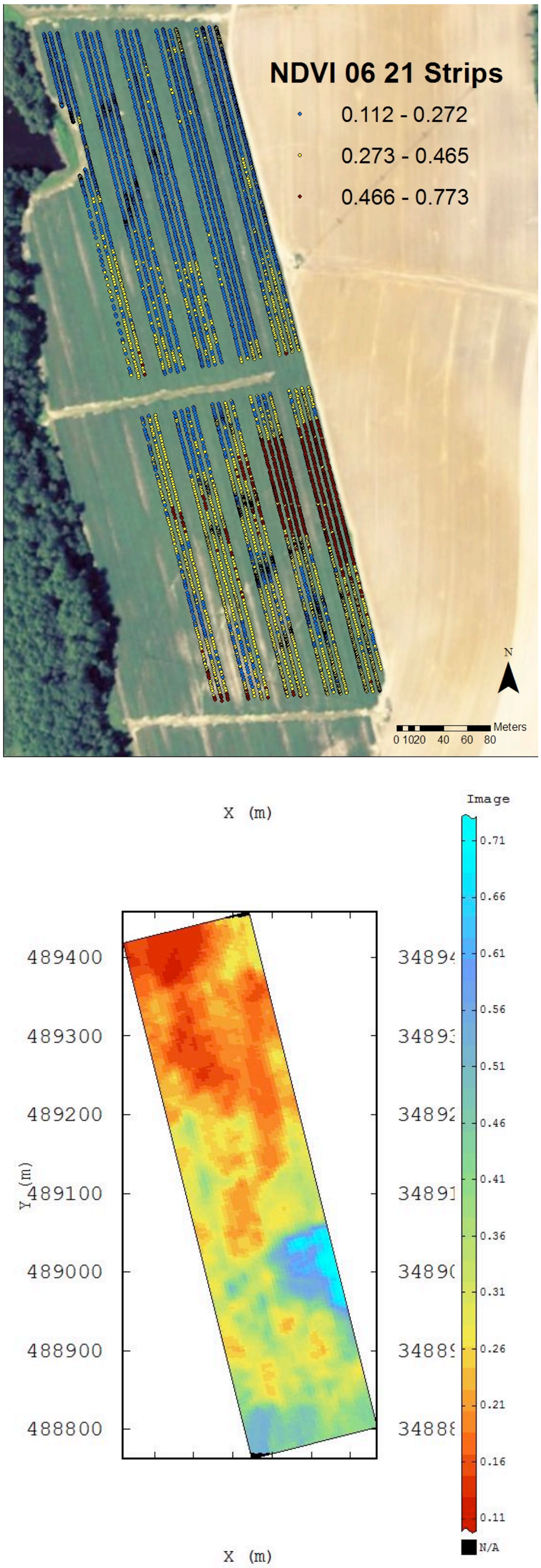


Figure 3.2 – Experimental results of NDVI and interpolated data by Kriging for June 21st

Sensing of June 21st (*Figure 3.2*) occurred 28 days after planting when emergence already occurred in both the high water (HW) and low water (LW) strips. Particularly, the dry weather caused poor growth, especially in the LW (northern field). By contrast, in HW (southern field), pivot provided higher water and consequently promoted crop growth.

This was clearly noticeable by NDVI distribution that did not exceed 0.272 in LW and that showed values frequently belonging to the high range (between 0.466 and 0.773) in HW.

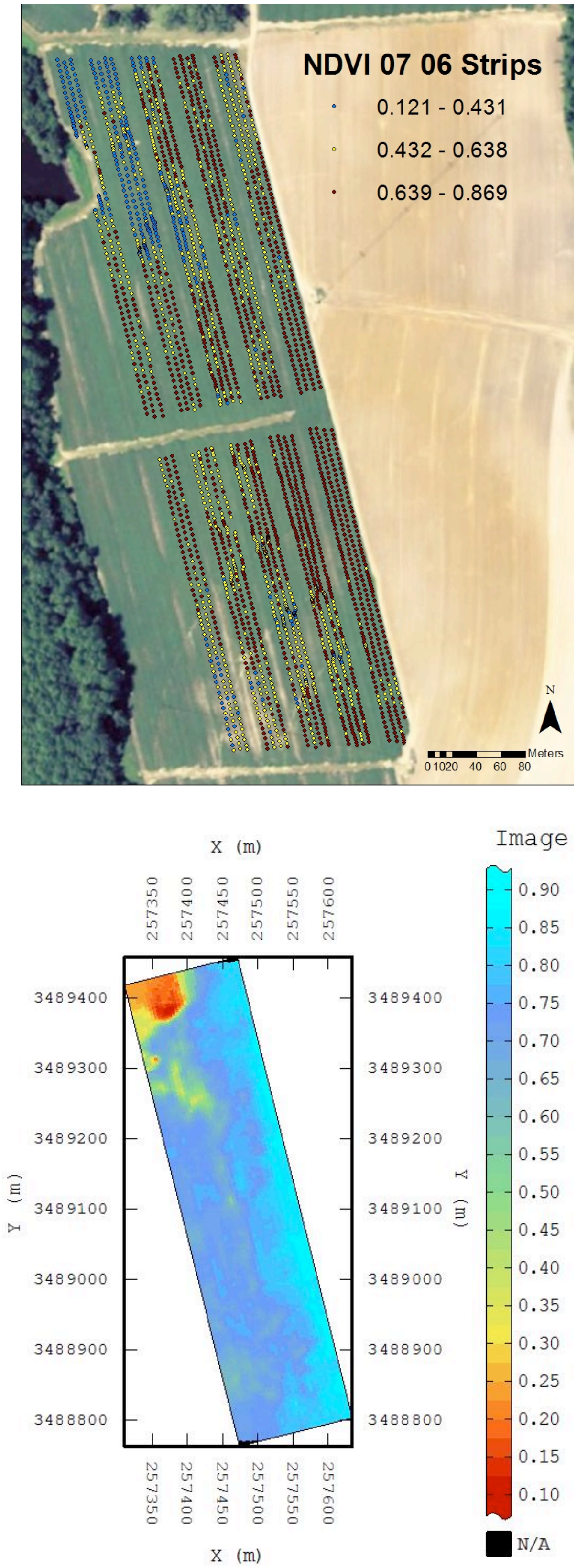
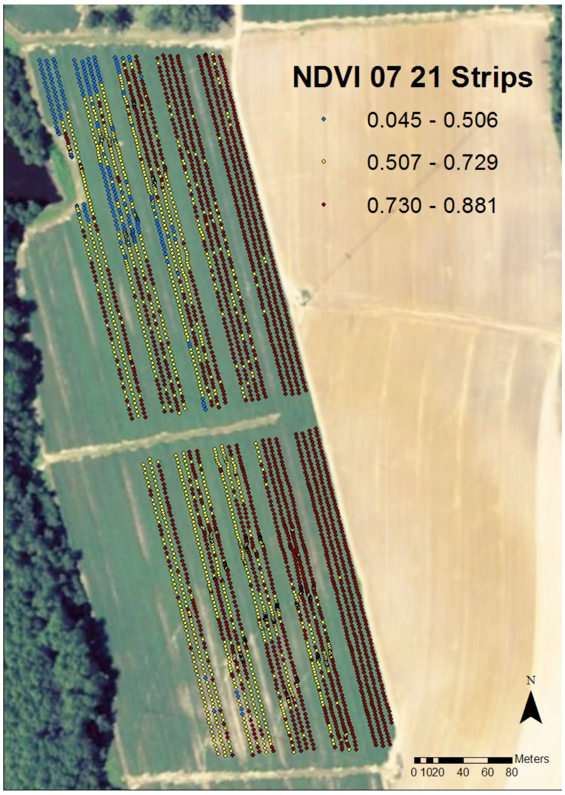


Figure 3.3 – Experimental results of NDVI and interpolated data by Kriging for July 6th

NDVI sensing map of July 7th (*Figure 3.3*) occurred 44 days after planting. North-west corner of LW evidenced critical low NDVI values due to water stress, which worsened with time, as it is showed in the last NDVI map (*Figure 3.4*).
LW blocks 1 and 2 (NE blocks) showed homogenous values belonging to high range. The remaining LW blocks presented heterogeneous NDVI values belonging from low to high ranges. Block 1 and 2 of HW (bottom right blocks) showed higher homogenous NDVI values, while the remaining ones were mostly represented by medium range NDVI values.



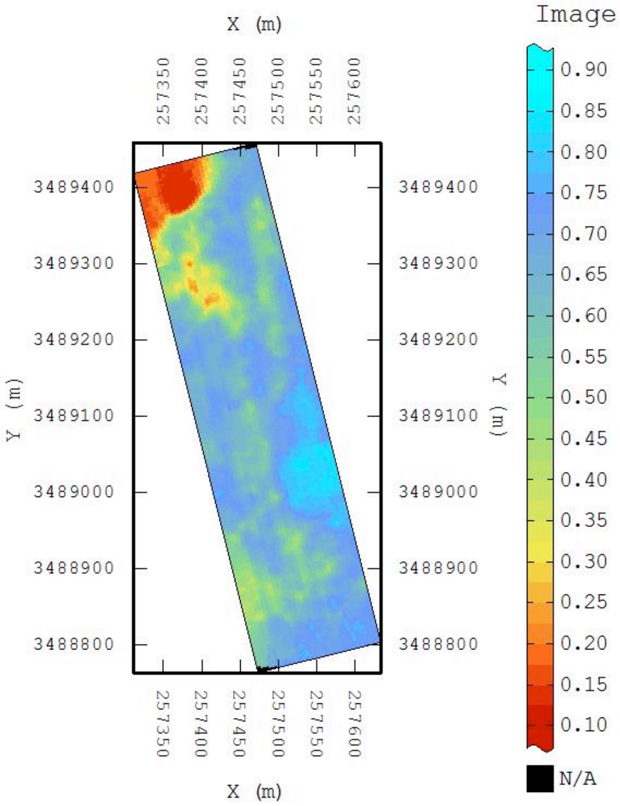


Figure 3.4 – Experimental results of NDVI and interpolated data by Kriging for July 21st

NDVI sensed in July 6th were classified according to three ranges by Farmworks® GIS Software (Trimble Navigation Limited, Sunnyvale, California, 2009). Average NDVI values were used to calculate variable rate application technology.

SBRNC model (*Eq. 2*), using NDVI data and the Clemson algorithm, allowed the estimation of nitrogen input (VRA1).

VRA2 was based on: a) historical records of yield and b) specific expertise of Agricultural Engineering Department (University of Georgia) that led the study.

3.2 LW Variable Rate Application

Table 3.2 – NDVI, INSEY, YP0, RI, VRA1 and VRA2 results relative to three NDVI average data of LW.

	Low NDVI	Medium NDVI	High NDVI
NDVI (Jul 7)	0.459	0.459	0.721
INSEY	0.011	0.014	0.017
YP0 (lbs/ac)	2204.12	3046.423	3988.00
RI	1.25	1.32	1.16
VRA1 (kg/ha)	49.54	87.09	58.06
VRA2 (kg/ha)	44.83	67.25	112.08

NDVI averages (*Table 3.2*) were used to estimate yield prediction (YP0) showing a high sensibility among the zones.

Indeed, VRA1 treatment strongly considered plant potential production; it assumes that a plant with low growth rate does not need a high fertilization dose; indeed crop stressed for other factors (e.g. water) could not have the ability to use efficiently the higher fertilizer input. This would result in nitrate loss and consequent negative economic and environmental impacts. VRA1 identified medium NDVI range as the most suitable to use high nitrogen amounts.

On the other hand, VRA2 assumed that more vigorous plants are the ones that can use more efficiently high nitrogen rates. Both VRAs tend to apply the minimum fertilizer rate to the poor growth plants.

3.3 HW Variable Rate Application

Table 3.3 – NDVI, INSEY, YP0, RI, VRA1 and VRA2 results relative to three NDVI average data of HW.

	Low NDVI	Medium NDVI	High NDVI
NDVI (6 Jul)	0.494	0.653	0.756
INSEY	0.011	0.015	0.018
YP0 (lbs/ac)	2385.815	3419.15	4405.58
RI	1.21	1.21	1.09
VRA1 (kg/ha)	46.74	64.34	44.83
VRA2 (kg/ha)	44.83	67.25	112.08

On average, HW showed higher NDVI than LW (*Table 3.3*); this resulted in higher crop yield potential (YP0). VRA1 applied the highest fertilization dose to medium NDVI range, while VRA2 applied the highest dose to high NDVI. As well as VRA1, estimated yield prediction (YP0) showed a large variability among the zones.

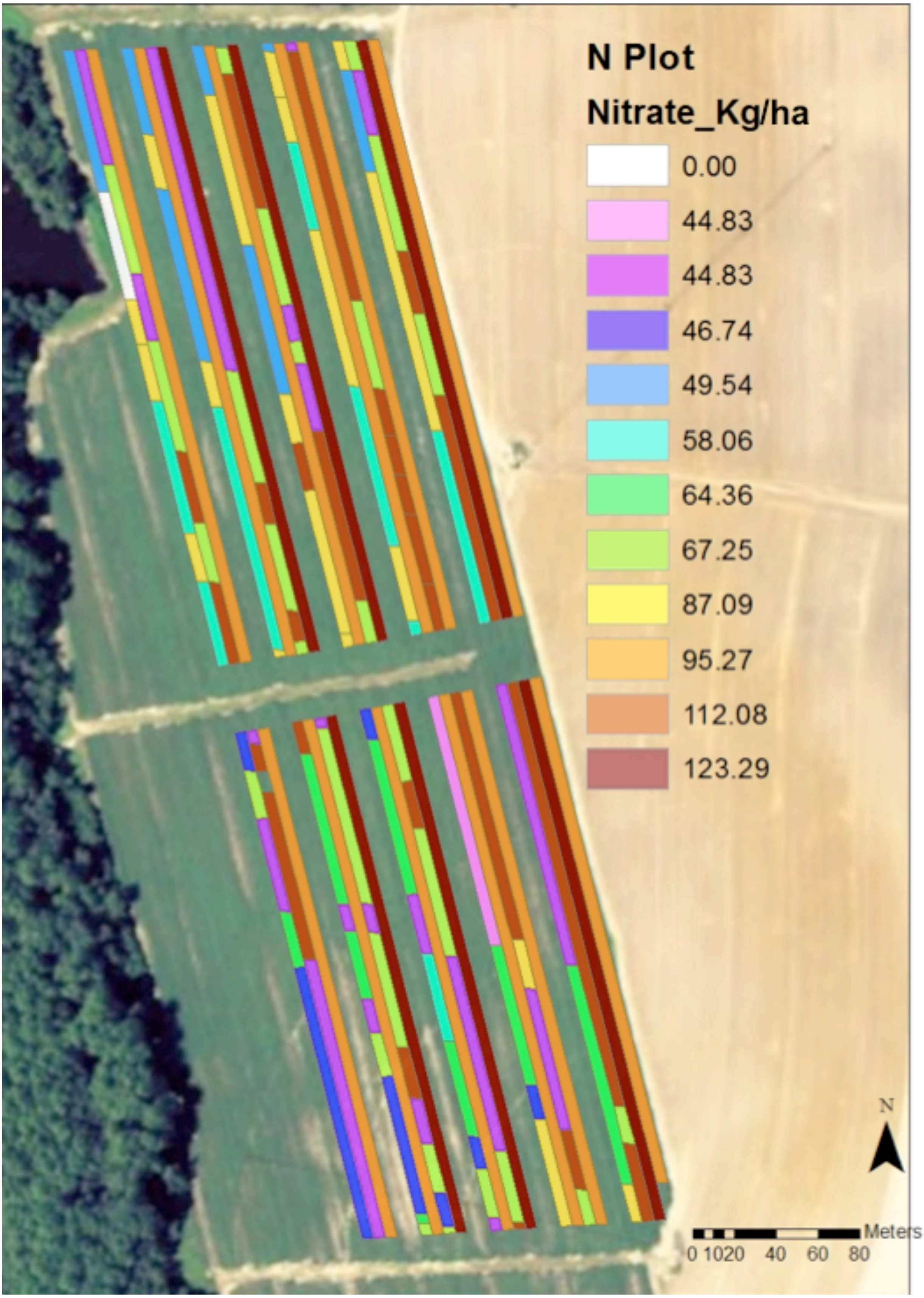


Figure 3.5 – Prescription map of variable rate fertilizations in the different plots (0 kg/ha N input was not considered for analysis)

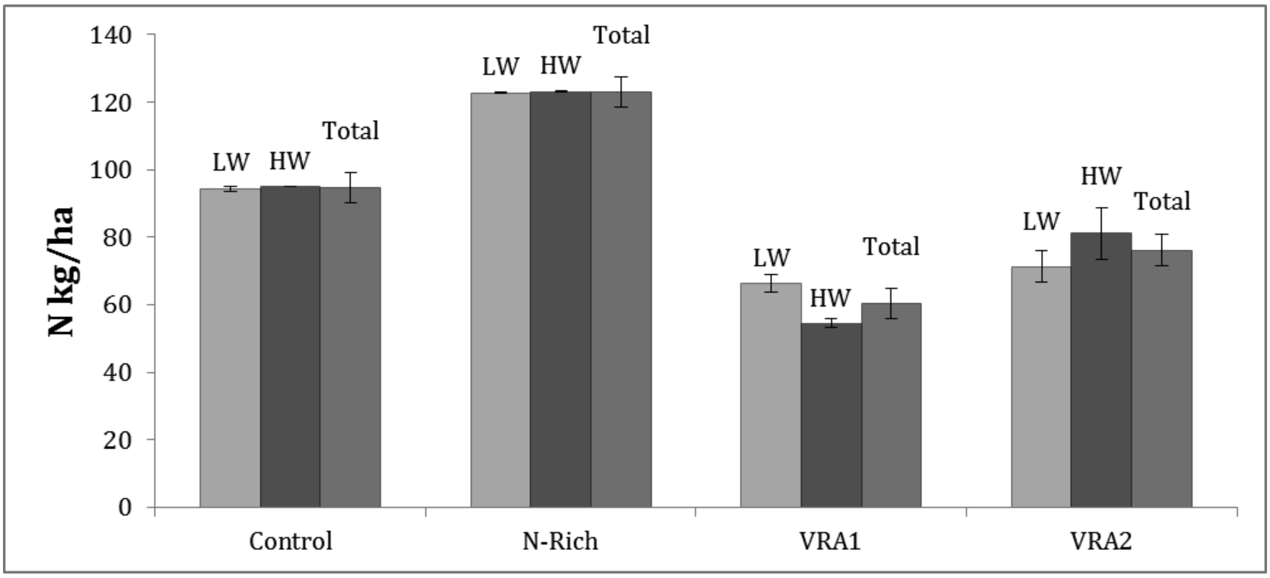


Figure 3.6, Table 3.4 – Nitrogen application kg/ha average low water field (LW), high water field (HW) and for the both (Total)

Treatment (N kg/ha)	LW	HW	Total
Control	94.45	95.09	94.77
N-Rich	122.77	123.18	122.98
VRA1	66.38	54.45	60.39
VRA2	71.37	81.09	76.23

Total values of N applied, including N-Rich treatment, ranged from 44.8 kg/ha to 124 kg/ha (*Figure 3.5*). With N-Rich treatment, as it was foreseeable, it was applied the highest dose (*Figure 3.6*). Control strips were interested by a lower fertilization rate than N-Rich treatment, although higher than the two VRAs. Variable rate applications, following crop needs, resulted in different agrochemical applications in LW and HW, on average. In both the strip, VRA1 was characterized by lower amounts of nitrogen than VRA2. N average input for VRA1 LW was about 66 kg/ha and it was about 54.5 kg/ha for HW. N average input for VRA2 LW was about 71.37 kg/ha whereas for HW N average input was about 81 kg/ha.

3.4 Cotton Yield

Cotton yield (lint + seed) showed high variability ranging from few kilograms/ha to values higher than 5000 kg/ha. As shown by the variogram (*Figure 3.7*) yield were correlated only within distance lower than 8 m. The lack of spatial correlation at higher distances could be due to VRA fertilization which smoothed the soil effect on cotton yield.

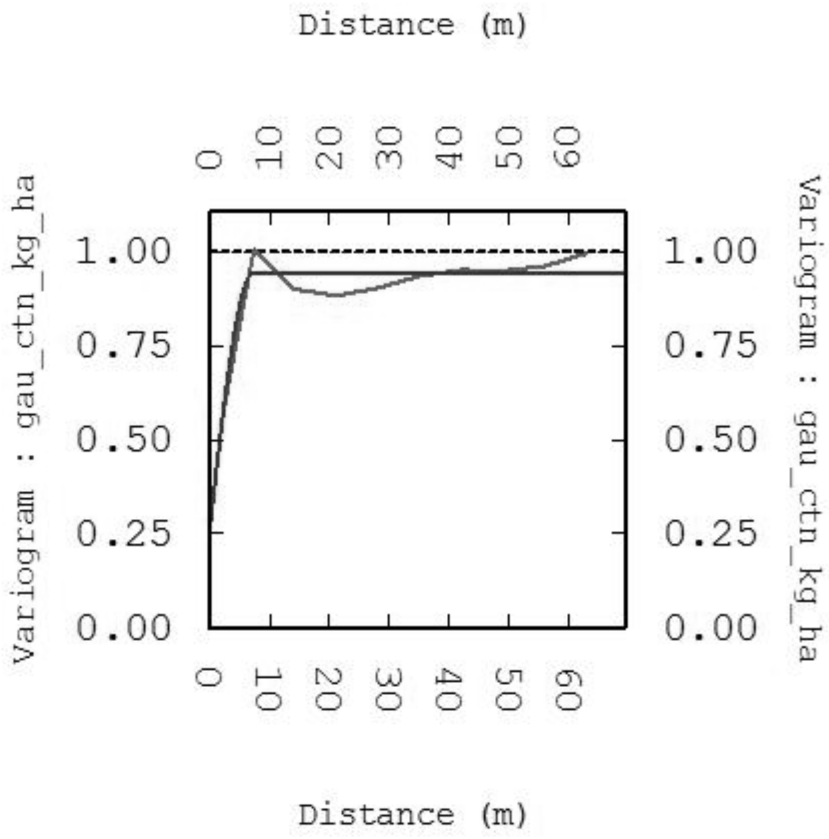


Figure 3.7 – Direct variogram of yield map data

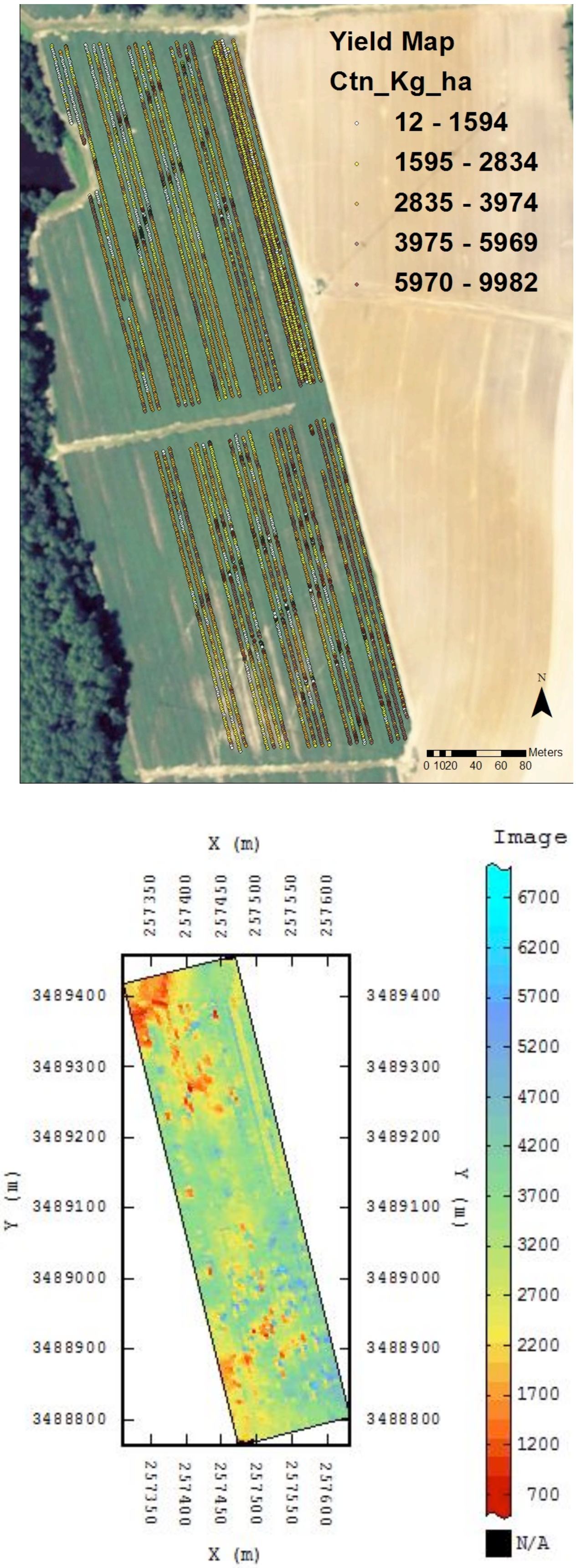


Figure 3.8 –Experimental data and Kriging modelling of yield map results

Yield map obtained by kriging (*Figure 3.8*) showed the effect of irrigation on the field. For example, lower yield was observed in the north west part which suffered of very low water application.

Water input was the only significant factor ($p<0.05$) with lower yield in LW (3164 kg/ha) than HW (3686 kg/ha) (Fig. 3.9) . Fertilization was not a significant factor, even if yield in Control was on average higher than other treatments (Fig. 3.10; tab.).

A significant interaction was instead observed between water input and fertilization ($P<0.05$).

Treatments did not show significant differences in LW while in HW yield in Control, N-rich and VRA-2 was higher than VRA1 (Fig. 3.11, tab. 3.3).

Most likely the higher N input applied in Control, N-Rich and VRA2 was able to exploit its effect only when combined with a correct irrigation (HW) (i.e. water factor was not limiting).

Worth to be noticed is the fact that high yield was obtained in VRA2 even if side-dressed N input (approx. 80 kg/ha) was lower than that of Control (approx. 100 kg/ha) and N-rich (approx. 120 kg/ha).

On the contrary, Clemson method (VRA1) underestimated the potential response of adjunctive N doses on cotton yield. In HW, NDVI-VRA1 was close to NDVI-N-rich and , according to the algorithm, this resulted in lower N input than that of LW (*Figure 3.6*).

When the water factor was limiting (LW) cotton did not take advantage of the higher N input and not significant differences were observed between the treatments.

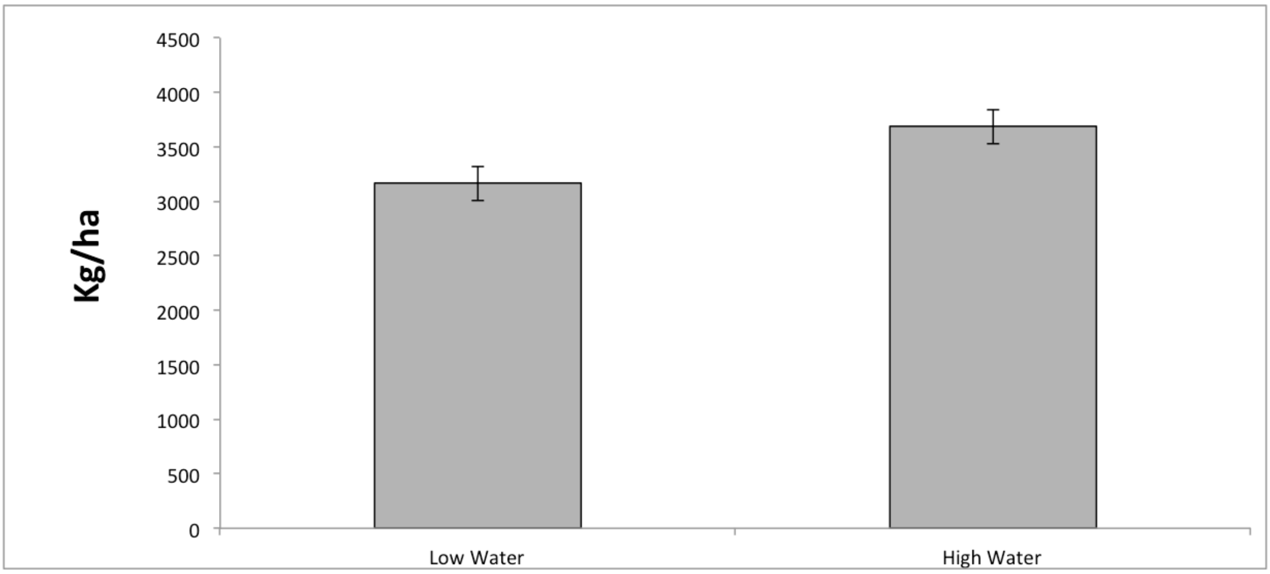


Figure 3.9 – Yield per field. Production refers both to lint and seed

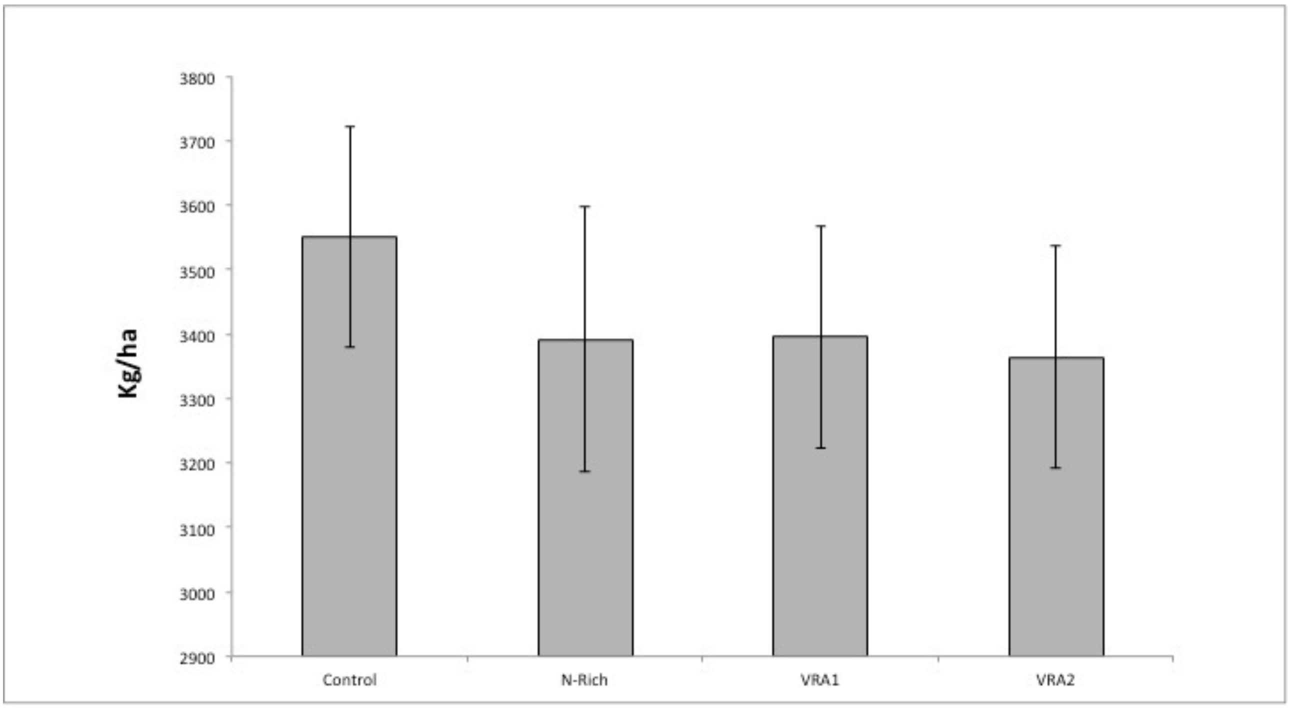


Figure 3.10 – Yield in the different treatments. Production refers both to lint and seed

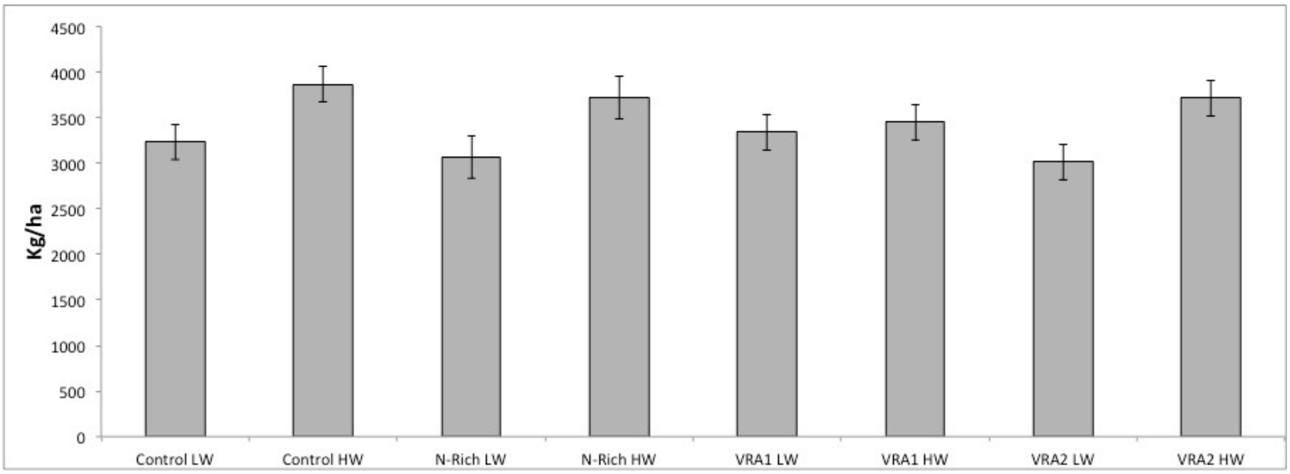


Figure 3.11 – Yield per field per treatment

Table 3.5 – Multiple comparison of yield per field between treatments (differences were underlined, P<0.05)

	Control LW	Control HW	N_Rich LW	N-Rich HW	VRA1 LW	VRA1 HW	VRA2 LW	VRA2 HW
Control LW		***<u>0.009</u>***	0.489	0.094	0.608	0.379	0.2785	0.062
Control HW			***<u>0.009</u>***	0.533	***<u>0.043</u>***	***<u>0.05</u>***	***<u>0.003</u>***	0.460
N_Rich LW				***<u>0.014</u>***	0.269	0.175	0.817	***<u>0.029</u>***
N-Rich HW					0.183	0.282	***<u>0.019</u>***	0.999
VRA1 LW						0.568	0.121	0.136
VRA1 HW							0.086	0.204
VRA2 LW								***<u>0.005</u>***
VRA2 Hw								

3.5 Nitrogen use efficiency

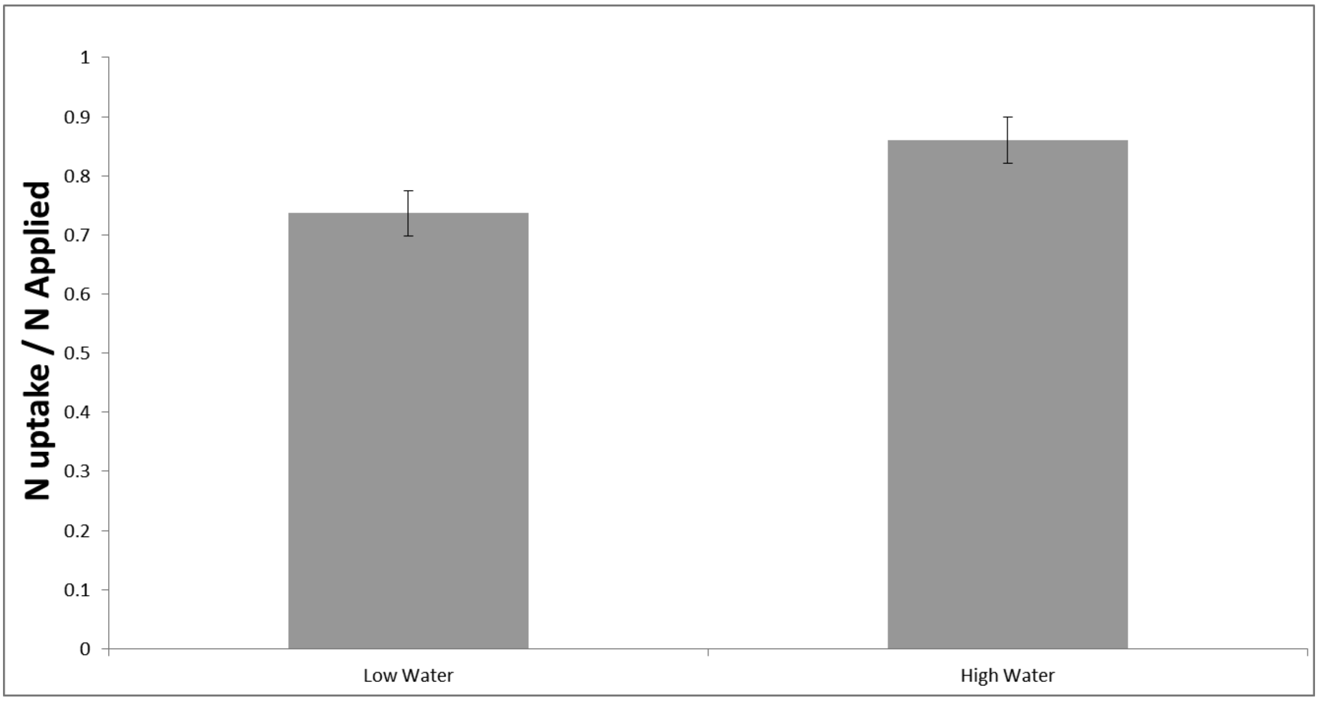


Figure 3.12 – Efficiency per water input

Both factors showed significant effects on N use efficiency (NUE). NUE was higher in HW (0.86) than LW (0.74) due to the higher N uptake promoted by the water availability. If efficiency was considered for each treatment, differences increased between treatments

(*Figure 3.13*). VRA1 showed value close to 1, higher than VRA2 (0.82) and Control and N-rich (0.74 and 0.56) . The low N-input in VRA-1 increased NUE with an probable positive effect on the environment. However if the interaction with water input is considered (*Figure 3.14*) (P<0.05), a critical condition is observed for VRA1 in HW. Indeed NUE assumes value around 1.1, indicating that an extra fraction of N was provided by the soil . In the long-term this condition could cause a non-sustainable exploiting of the soil fertility.

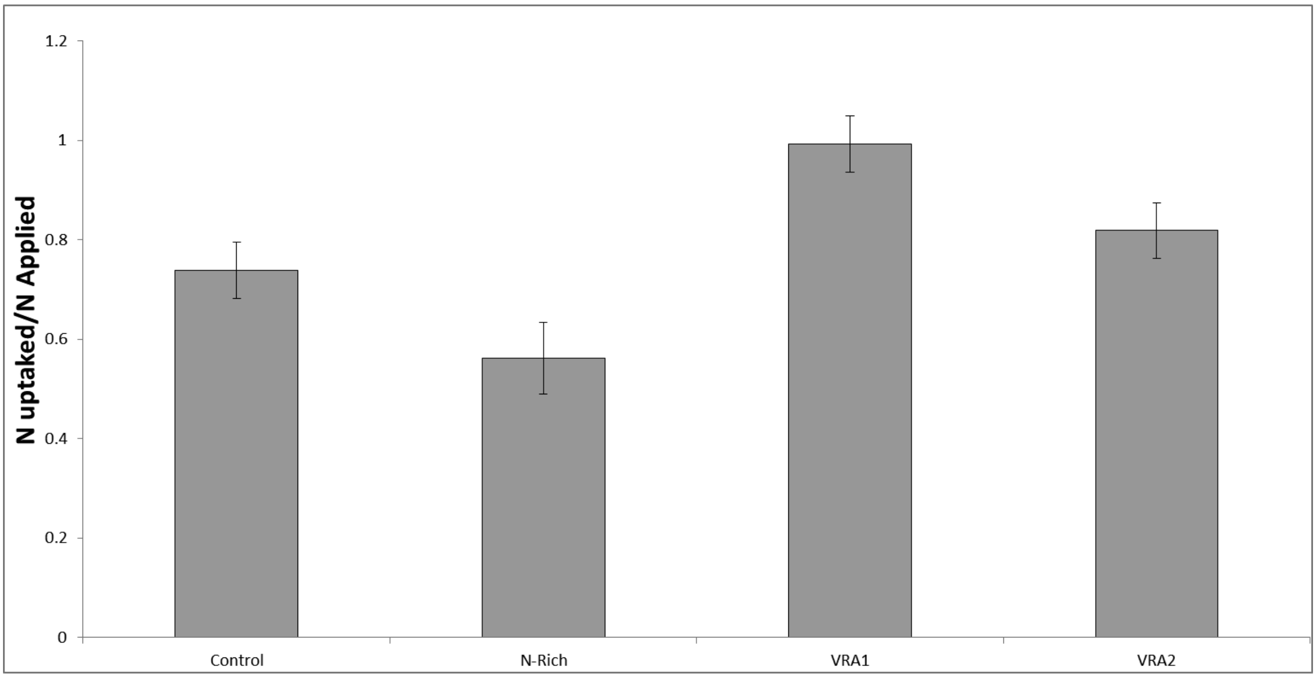


Figure 3.13 – NUE per treatment

Table 3.6 - Multiple comparison of treatments efficiency (differences were underlined, P<0.05)

	Control	N-Rich	VRA1	VRA2
Control		0.460	***<0.0001***	***<0.05***
N-Rich			***<0.0001***	***0.0006***
VRA1				***0.002***
VRA2				

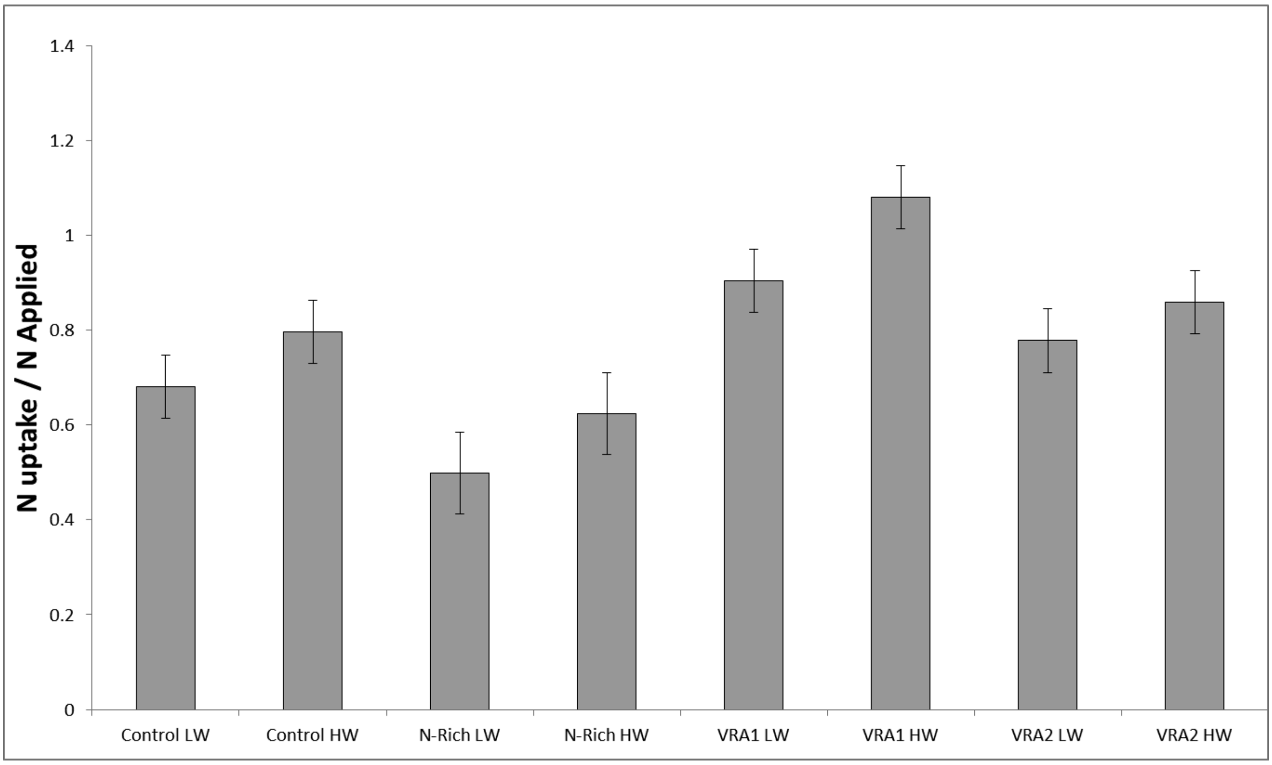


Figure 3.14 - Efficiency per field per treatment

At the same time, in LW, N-Rich and Control had a low NUE (<0.7), since they provided a surplus of nitrogen not used by the crop. Only VRA2 was able to assure a reasonable NUE in both water input conditions and for this reason it appears to be the best compromise between agronomic and environmental issues.

Table 3.7 – Multiple comparison of treatments efficiencies for each field differences were underlined, P<0.05)

	Control LW	Control HW	N_Rich LW	N-Rich HW	VRA1 LW	VRA1 HW	VRA2 LW	VRA2 HW
Control LW		0.056	***0.0396***	0.4337	***0.0004***	***<0.0001***	***0.036***	***0.0069***
Control HW			***0.0017***	***0.0357***	***0.0212***	***<0.0001***	0.5741	0.1794
N_Rich LW				0.1413	***<.0001***	***<0.0001***	***0.0005***	***<0.0001***
N-Rich HW					***0.0002***	***<0.0001***	***0.013***	***0.0024***
VRA1 LW						***0.0007***	0.0645	0.2751
VRA1 HW							***<0.0001***	***0.0002***
VRA2 LW								0.3307
VRA2 HW								

Plant yield response to different N input in VRA was reported in *Figures. 3.15, 3.16, 3.17, 3.18*. Crop production did not present significant correlation with N input, neither in low water nor in high water . The lack of significant relationship could be due to the VRA that modulated the doses according to the soil fertility, smoothing the effect of the soil variability.

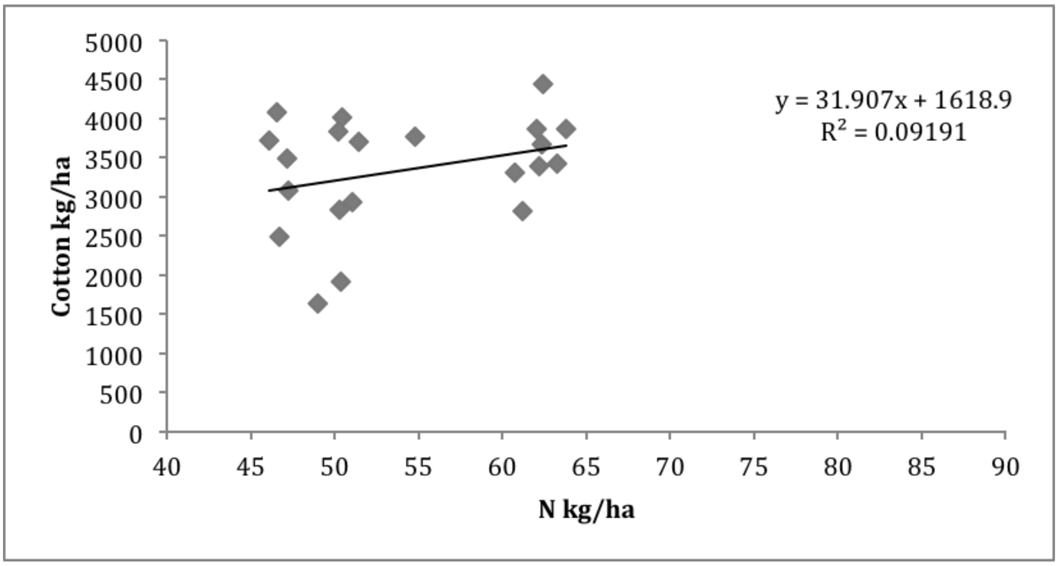


Figure 3.15 – Relationship between N input and product harvested relative to VRA1 in LW

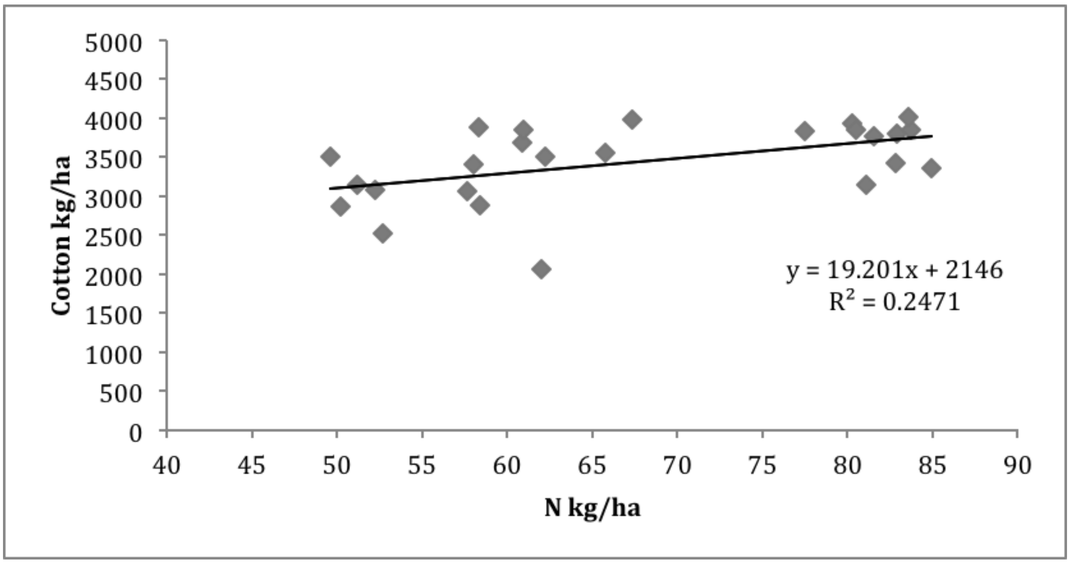


Figure 3.16 – Relationship between N input and product harvested relative to VRA1 in HW

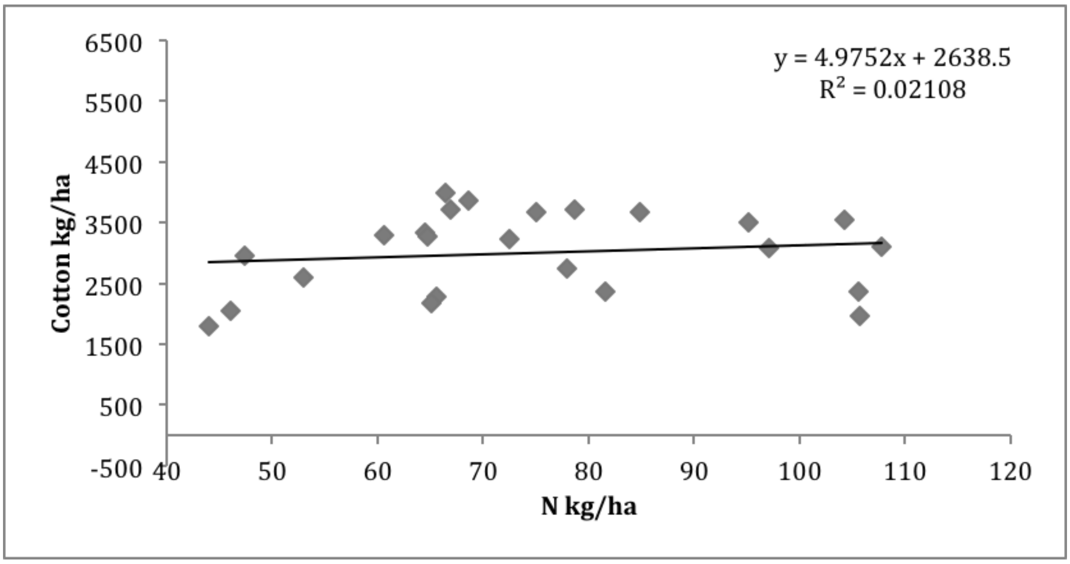


Figure 3.17 – Relationship between N applied and product harvested relative to VRA2 in low water field

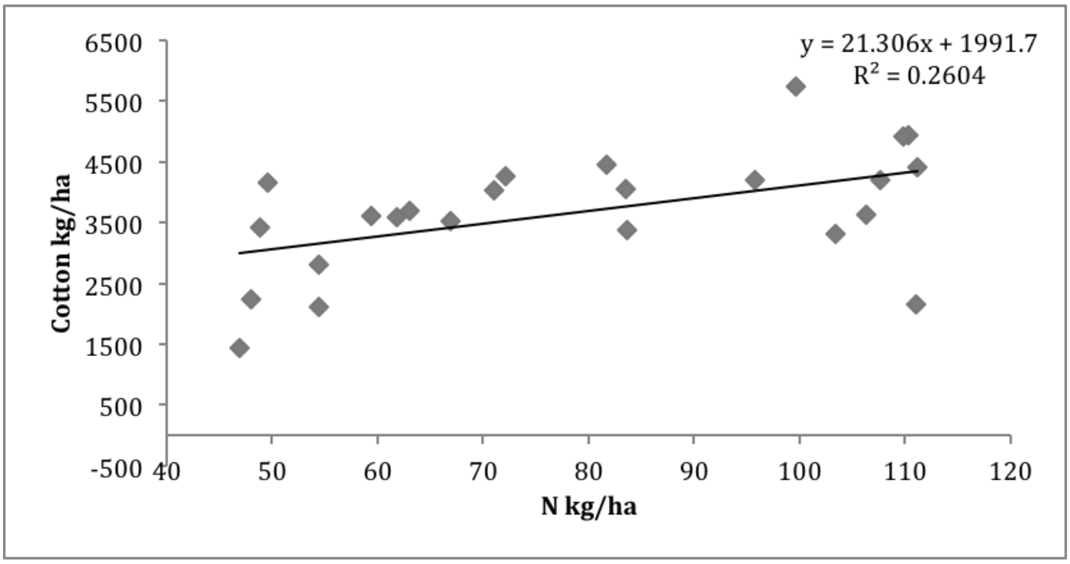


Figure 3.18 – Relationship between N applied and product harvested relative to VRA2 in high water field

3.6 Economic balance

The economic balance was calculated at field scale by the difference between the gross product and fertilizer cost. Cotton lint price was assumed to be 3.08 $/kg (1.4 $/lbs) (Georgia cotton production guide, 2012) while UAN cost was 0.44 $/kg.

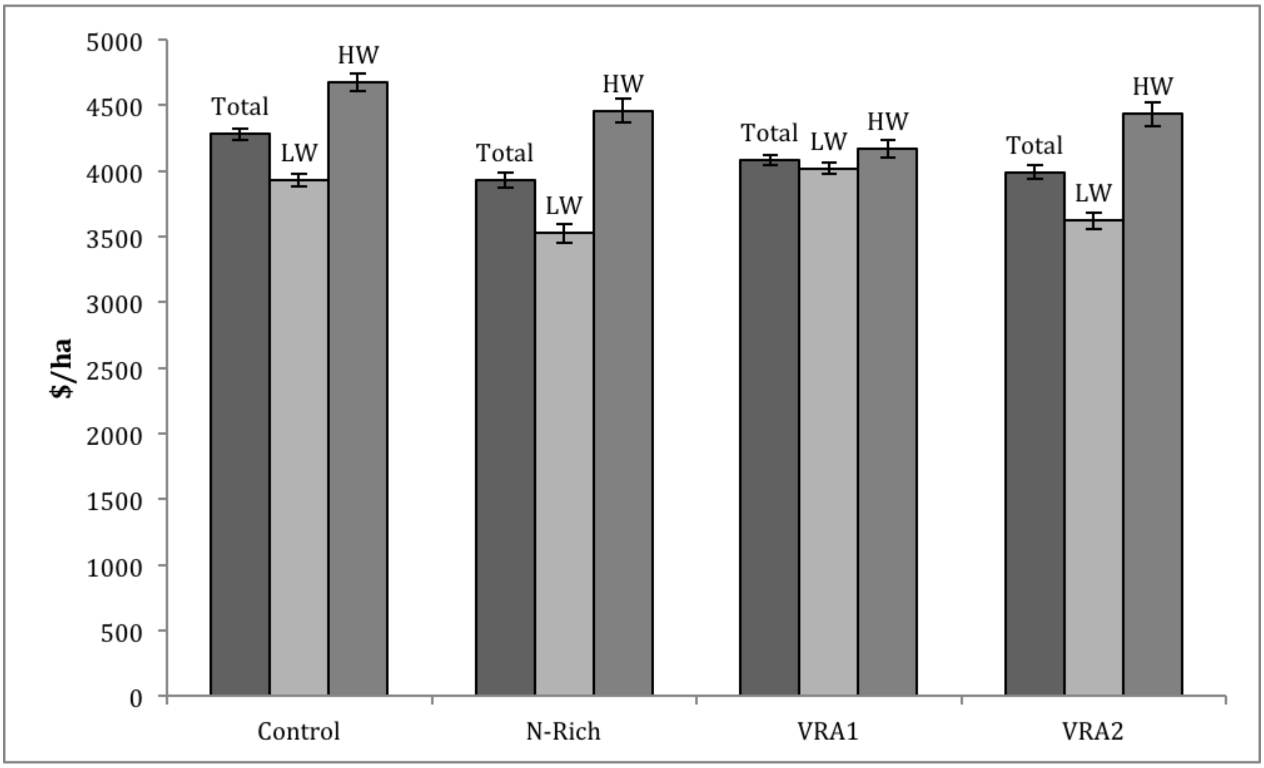


Figure 3.19 – Economic pay-off per each treatment considered per each field (LW, HW) and for the both (Total)

On average, no significant differences were observed between the treatments. Larger differences are observed if results are analyzed according to water input. In LW, VRA1 seemed the most profitable management practice; this could be due to the lower N input that reduced the costs of fertilization. In HW, on the contrary, VRA1 is the lower profitable treatment, while VRA2, Control and N-Rich gained higher profits. This confirmed that without water limiting condition crop was able to use larger N quantities, resulting in higher yields As a result better economic performances were achieved with higher N input.

4 Conclusions

Agronomic and economic performances of VRA were influenced by the interaction of the N input with other crop-yield limiting factors (i.e. water availability).

VRA based on Clemson University algorithm (VRA1) showed the best environmental performances since it allowed to increase the nitrogen use efficiency reducing at the same time the potential N losses. This result was achieved by mean of a general reduction of N input which did not have a depressive effect on crop yield in low water input strip (LW). On the contrary VRA1 in high water (HW) strip did not take into account the higher crop-growth potential, resulting in a lint production lower than the other treatments.

Nitrogen use efficiency in VRA2 was lower than VRA1 especially in water stress conditions. VRA2 in LW could have increased the risk of N pollution. Conversely VRA2 in HW allowed to obtain yields comparable to Control but with a lower N input that conventional treatment.

NDVI was sensible to vegetation status allowing driving the site-specific application of fertilizer. Some doubts about its efficiency arouse observing the low index variability in the high-value range. In these conditions NDVI could be not enough sensible to assess canopy differences. This could suggest considering earlier sensing times, when crop canopy is not fully developed, as the most suitable for VRA application.

Generally, results demonstrated a better environmental performance of both the VRAs. VRA1 appears to be more appropriate for water stress conditions, allowing reducing N input without depressing crop yield. When water is not a limiting factor, VRA2 offers more advantages to the farmers.

This study did not take in consideration technological and environmental costs. A more specific nitrogen balance could be helpful to improve the evaluation of VRA on different point of views. Moreover, further and specific analysis on irrigation could be needed to understand nitrogen soil allocation and treatments efficiency.

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